Journal of Sustainable Development and Policy

Volume: 1; **Issue:** 2
Pages: 87-133

DATA-DRIVEN PROCESS OPTIMIZATION IN AUTOMOTIVE MANUFACTURING A MACHINE LEARNING APPROACH TO WASTE REDUCTION AND QUALITY IMPROVEMENT

Md. Foysal Hossain[1]; Subrato Sarker[2];

[1]. *Industrial Engineer, Bangladesh Honda Private Limited (Japanese Automobile HONDA), Bangladesh; Email: foysal.hossain.ipe@gmail.com*

[2]. *Manager, Daraz, Dhaka, Bangladesh*
Email: subrato120@gmail.com

Doi: 10.63125/2hk0qd38
***Received:** 18 March 2022; **Revised:** 17 April 2022; **Accepted: 17** May 2022; **Published:** 28 June 2022*

Abstract
Data-driven process optimization in automotive manufacturing was examined as a quantitative approach for reducing waste and improving product quality by linking integrated production, quality, maintenance, and batch-traceability data with measurable outcomes. The study was positioned through a structured review of 35 peer-reviewed papers and was executed as a retrospective case analysis using 48,720 eligible production-unit records joined by unit ID, station identity, and synchronized timestamps. Descriptive findings indicated scrap occurrence of 2.60% (n = 1,268), rework routing of 12.55% (n = 6,112), first-pass yield of 87.45% (n = 42,608), and defect occurrence of 6.15% (n = 2,994) at the selected inspection gate; defect cases were distributed across dimensional 36.0% (n = 1,077), weld 24.0% (n = 718), surface/paint 22.0% (n = 659), and functional 18.0% (n = 540) categories. Correlation analysis showed that rework hours per unit were positively associated with torque deviation (r = 0.46) and dimensional deviation (r = 0.41) and negatively associated with a sensor-based stability index (r = −0.38). Measurement reliability supported quantitative interpretation, including inspection label agreement of 0.97, defect-category consistency (κ = 0.78), and high repeatability for key trace-derived indicators (ICC = 0.89). Collinearity screening identified redundancy among correlated telemetry summaries, with maximum VIF reduced from 9.6 to 3.6 after consolidation. Regression results indicated higher defect odds with torque deviation (OR = 1.28, 95% CI [1.21, 1.35]) and dimensional deviation (OR = 1.42, 95% CI [1.31, 1.54]), while stability reduced defect odds (OR = 0.81, 95% CI [0.77, 0.85]). Block wise modeling showed improved explanatory power from context-only (adjusted R^2 = 0.08) to full models including process, equipment, and batch predictors (adjusted R^2 = 0.33), supporting an integrated quantitative framework for waste reduction and quality improvement.

Keywords
Data-driven optimization, Machine learning, Automotive manufacturing, Waste reduction, Quality improvement.

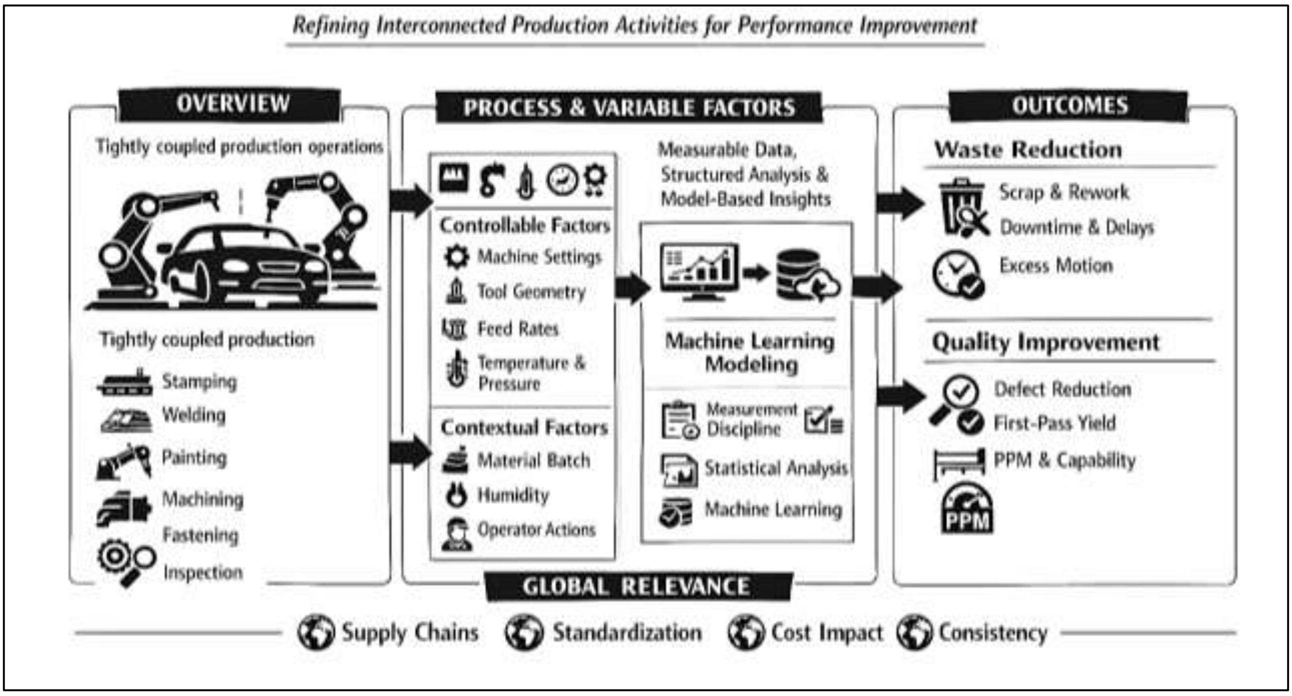
INTRODUCTION

Manufacturing process optimization is defined as the systematic, measurement-centered refinement of interconnected production activities so that performance improves in observable and verifiable ways. In automotive manufacturing, this definition applies to tightly coupled operations that transform raw materials into complex assemblies through stamping, welding, painting, machining, fastening, and final inspection (Petrillo et al., 2019). Each operation contains controllable variables, such as machine setpoints, tool geometry, feed rates, temperature, pressure, torque, and sequencing rules, along with contextual variables such as material batch properties, humidity, operator actions, and equipment aging. Process optimization becomes quantitative when these factors are represented as variables and linked to measurable outcomes. Waste reduction is defined as the measurable elimination of non–value-adding resource consumption, including scrap, rework, excess motion, waiting time, unnecessary transport, overprocessing, inventory accumulation, avoidable downtime, and repeated inspection loops (Arfan et al., 2021). Quality improvement is defined as the measurable reduction of defects and variability while increasing the stability of outputs relative to engineering specifications and functional requirements. These constructs are typically expressed through indicators such as first-pass yield, scrap rate, rework hours per unit, defect density, parts-per-million nonconformance, cycle time, line stoppage frequency, mean time between failures, and process capability indices derived from dimensional or functional measurements. International significance emerges because automotive manufacturing is organized through global supply chains and multi-plant production strategies that rely on standardized product platforms, shared component architectures, and internationally harmonized safety and compliance expectations (Jahid, 2021; Lim, 2019). A small percentage change in defect rate or scrap volume within one plant can correspond to substantial material savings and quality consistency when scaled across high-volume output and replicated across regions. Moreover, global supplier networks mean that incoming quality variation and part interchangeability influence waste and quality performance across borders. In this setting, data-driven process optimization is not a local exercise only; it is embedded in global competitiveness, delivery reliability, and consistent customer experience (Akbar & Farzana, 2021). Quantitative research approaches treat the manufacturing line as a measurable system in which inputs, transformations, and outputs can be represented through distributions, correlations, and modeled relationships, allowing improvement initiatives to be evaluated using numerical evidence rather than informal judgment (Nicoletti, 2016; Reza et al., 2021).

Classical quantitative approaches to optimization in automotive manufacturing are rooted in measurement discipline, variation analysis, and structured improvement cycles that define performance as something that can be monitored, tested, and verified. Statistical monitoring frameworks interpret production data as signals that reflect underlying process stability, separating common-cause variation from special-cause shifts that require investigation (Bécue et al., 2020; Zobayer, 2021a). In practical terms, this includes the use of time-ordered measurements, subgrouping logic, and structured rules for identifying abnormal patterns in key variables such as torque values, weld current, coating thickness, dimensional gaps, or functional test readings. Capability analysis translates measurement distributions into conformance probabilities, enabling quantitative descriptions of how well a process meets specification limits under current conditions.

Industrial experimentation further supports optimization by estimating factor effects and interactions through controlled variation in settings, fixtures, or materials, producing measurable evidence regarding which changes reduce defects, shorten cycles, or decrease scrap. In automotive assembly environments, the value of these methods grows because small deviations can propagate through downstream stations, generating compounded rework loops and hidden quality costs (Kumar et al., 2018; Zobayer, 2021b). Lean-oriented measurement traditions complement statistical techniques by quantifying waste through time studies, work balance metrics, changeover durations, work-in-process inventories, and rework routing frequencies. These measures establish numerical visibility into flow inefficiencies, queue formation, and repeated handling, all of which translate into throughput losses and resource waste. Maintenance-focused measurement systems add another layer by quantifying availability losses, minor stoppages, speed losses, and quality losses, connecting equipment condition and maintenance practices to downstream defect rates and scrap generation. Structured improvement cycles frame these measurement tools into repeatable sequences that emphasize defining the problem quantitatively, measuring reliably, analyzing with appropriate statistical logic, improving via tested adjustments, and controlling through ongoing monitoring. Internationally, these practices are relevant because they provide shared performance languages across plants that build similar vehicle platforms, enabling cross-site comparability in metrics, defect taxonomies, and improvement verification. As automotive firms operate under supplier diversity and regional constraints, measurement-based frameworks remain central because they reduce ambiguity: improvement is demonstrated through verified changes in indicators rather than through narrative descriptions, allowing operations to be managed with consistent numeric standards across global systems.

Figure 1: Data-Driven Automotive Manufacturing Optimization

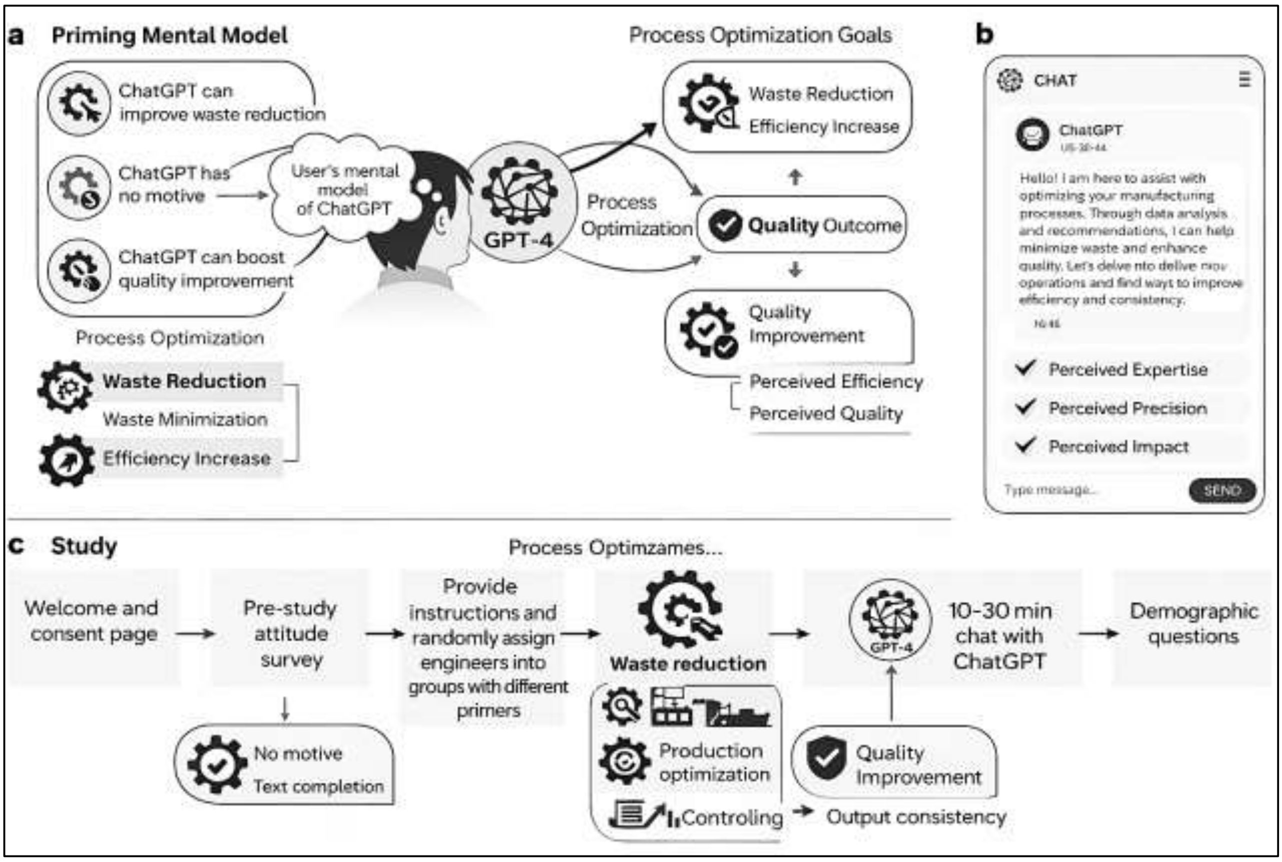


The expansion of digital instrumentation and integrated data capture has increased the feasibility of computational modeling in automotive manufacturing, creating the conditions for machine learning approaches that leverage large-scale production data. Machine learning is defined as a class of methods that learn patterns from data to improve predictive or descriptive performance on specified tasks, using empirical relationships rather than fixed rule sets (Ariful & Ara, 2022; Thakkar, 2020). In automotive production, these tasks often include predicting defect occurrence, classifying defect types, estimating dimensional deviation, identifying abnormal process states, detecting drift, and modeling the likelihood of scrap or rework under given conditions. Supervised learning is commonly used when labeled outcomes exist, such as pass/fail inspections, defect codes, or measured deviations from targets. Unsupervised learning is used when labels are incomplete or when the objective is to identify latent structure, such as clusters of operating modes, anomalous sensor combinations, or shifts in multivariate behavior (Arman & Kamrul, 2022). Some approaches model sequences and temporal dependency, which is important in environments where tool wear, temperature stabilization, and batch transitions change the process state over time. Deep learning methods are applicable when inputs are high-dimensional, including image-based surface inspection, acoustic signatures of equipment condition, or multichannel time-series from welding and machining (Niu, 2017). From a quantitative standpoint, the central premise is that many waste and quality outcomes are functions of interactions among numerous variables, and computational methods can represent non-linear relationships that are difficult to specify in simple parametric forms. Model evaluation is conducted using measurable performance metrics such as classification accuracy, precision, recall, false alarm rates, probability calibration, and error distributions for continuous predictions. This evaluation becomes meaningful when connected to operational cost structures, where different error types correspond to different waste pathways, such as unnecessary rework, missed defects, or excess inspection. International significance is present because multi-plant operations share product architectures but face local variability in materials, equipment maturity, and environmental conditions. Data-driven models can be trained to reflect local realities while using standardized variable definitions and comparable evaluation criteria, supporting consistent measurement across global production footprints (Moldavska & Welo, 2018). In such settings, machine learning is positioned as a quantitative instrument for mapping complex process data to measurable waste and quality outcomes, with performance verified through rigorous testing rather than assumed through intuition.

Waste and quality loss in automotive manufacturing typically arise through multistage interactions that link upstream variation to downstream assembly constraints, producing measurable consequences in scrap, rework, line stoppages, and final conformance outcomes (Reinkemeyer, 2020). A vehicle is assembled through many dependent steps, and variation introduced at one station can increase the probability of nonconformance at subsequent stations, especially when tolerances stack and assemblies require precise alignment. In body structure production, for example, weld quality and dimensional stability depend on electrode wear, clamping consistency, surface conditions, material thickness variability, thermal distortion, and sequence timing. These factors influence measurable outputs such as nugget size consistency, joint strength proxies, gap-and-flush metrics, and dimensional audit readings. In paint operations, measurable defects such as runs, orange peel, pinholes, adhesion issues, and color inconsistencies can be connected to variables including viscosity control, spray pressure, booth airflow stability, environmental humidity, curing profiles, and filtration performance. In machining and component manufacturing, quality outcomes such as surface roughness, concentricity, and dimensional tolerance adherence are influenced by tool wear, spindle vibration, coolant condition, machine thermal behavior, and fixturing stability, creating measurable drift patterns that can be traced through time-series and inspection datasets (Accou & Reniers, 2020). Waste is not limited to material loss; it includes repeated handling, transportation between buffer areas, waiting caused by imbalanced stations, and rework loops that consume capacity and create additional variability. Supplier variation further contributes when incoming parts exhibit dimensional drift or material property deviations, raising defect probabilities and increasing inspection intensity. A data-driven approach integrates these interdependent mechanisms by linking heterogeneous datasets, such as incoming inspection records, in-process sensor streams, maintenance logs, rework routing histories, and end-of-line test outcomes. Machine learning methods become relevant because they can capture interactions across domains, such as the combined effect of tool age and material batch, or the joint effect of humidity and curing time, which may not be evident through univariate screening (Merkt, 2019). Internationally, these mechanisms recur across plants that build similar platforms and use comparable process technologies, making the identification of measurable drivers of waste and defects important for consistent performance tracking across regions. The quantitative objective is to represent these multistage relationships in models that connect controllable variables to measurable outcomes, enabling precise identification of where waste and quality loss are generated along the process chain.

A rigorous quantitative study in machine-learning-driven process optimization depends on clear definitions of data structures, measurement reliability, variable operationalization, and evaluation protocols that support verifiable claims about model performance (Bakri & Januddi, 2020). Automotive manufacturing data can be categorized into continuous process measurements such as current, voltage, pressure, temperature, torque, vibration, and flow rates; discrete events such as alarms, stops, resets, and changeovers; categorical context variables such as shift identifiers, line identifiers, operator teams, supplier codes, and product variants; and unstructured inputs such as images, audio, and text-based defect notes. Each category requires specific handling to ensure that the resulting dataset preserves meaningful signal. Data quality is central because measurement noise, inconsistent sampling, missing values, and label ambiguity can distort estimated relationships. Defect labels may vary by inspector interpretation, inspection station sensitivity, and rework coding practices, so the study must treat labeling consistency as a quantitative concern tied to reliability. Variable construction is also fundamental: raw sensor values may not represent the true process state without aggregation, filtering, lagging, and feature extraction that align signals with the physical events that generate quality outcomes. For supervised learning, response variables must be defined precisely, such as binary nonconformance, multiclass defect categories, continuous deviation magnitudes, or cost-weighted loss measures reflecting scrap and rework. Model validation must be designed to avoid inflated performance estimates caused by data leakage or dependence structures, which are common when observations share batch, shift, or equipment states (Arman & Kamrul, 2022; Mesbaul & Farabe, 2022; Salimi & Salimi, 2017). Temporal splitting can be necessary when the process evolves over time, and grouped validation can be necessary when part families or line segments have shared signatures (Abdur & Haider, 2022; Mushfequr & Praveen, 2022). Performance metrics must align with operational priorities: rare critical defects require sensitivity measures, high false alarm rates create inspection waste, and poorly calibrated probabilities reduce decision usefulness when thresholds determine rework routing. Interpretability is treated as a quantitative requirement because actions must map to controllable variables (Mortuza & Rauf, 2022; Rakibul & Samia, 2022); therefore, variable influence summaries, local decision explanations, and stability checks across operating regimes are relevant components of evidence. International operations add complexity because measurement architectures and coding schemes can differ across regions, making standardization of definitions and preprocessing steps essential for comparability. Within this structure, the quantitative focus remains on how data are transformed into analyzable variables, how models are evaluated under realistic constraints, and how measured performance is reported in ways that connect to waste reduction and quality improvement indicators (Vichard et al., 2020).

Figure 2: AI-Driven Manufacturing Process Optimization



Machine learning methods operate within a broader quantitative modeling landscape that includes classical regression, multivariate monitoring, clustering, and hybrid modeling approaches that blend domain structure with empirical flexibility. Regression-based models provide baselines for estimating directional effects and interaction terms with transparent parameter interpretation, which is valuable when process engineers require clear mappings between factors and outcomes (Pakdil, 2020). Multivariate monitoring methods represent correlated sensor systems through lower-dimensional structures that can detect shifts across many variables simultaneously, supporting the identification of process state changes that may lead to waste and defects. Clustering and anomaly detection methods provide additional quantitative tools for identifying latent regimes, such as stable production modes, transitional states during changeovers, or abnormal combinations of settings that precede nonconformance. In automotive manufacturing, observational data often include confounding patterns that arise from operational interventions, such as increased inspection following known issues, targeted maintenance during high-risk periods, or parameter adjustments that occur in response to early defect signals. Quantitative designs therefore require attention to sampling frames and documentation of intervention points, so that model learning reflects process behavior rather than surveillance artifacts. Hierarchical structure is also prominent: parts are produced within batches, batches within shifts, shifts within lines, and lines within plants, creating dependence that affects generalization if not addressed through grouped sampling or multilevel representations. Maintenance analytics contributes predictors that quantify equipment health, including vibration indicators, lubrication status, temperature drift, and historical failure patterns, which can be linked to both quality outcomes and waste pathways (Rathore et al., 2020). Automated inspection systems increase the resolution of measurable quality signals, generating richer outcome variables and enabling earlier detection of defect formation. Data fusion across these sources expands the dimensionality of the analytical problem and creates opportunities for models that identify cross-domain interactions, such as how maintenance condition modifies the effect of process settings on defect probability. International manufacturing contexts magnify the relevance of robust quantitative methodology because plants differ in equipment age distributions, supplier portfolios, environmental conditions, and workforce routines. A consistent modeling approach requires standardized variable definitions and evaluation structures so that differences in results reflect true process differences rather than measurement inconsistencies (Usuga Cadavid et al., 2020). Within this methodological environment, the introduction to a quantitative paper remains centered on defining measurable constructs, clarifying modeling tasks, and specifying how evidence is generated through validated performance metrics and structured comparisons across relevant operating conditions.

Within a quantitative framing, waste reduction and quality improvement are specified through measurable changes in resource consumption, time utilization, and conformance distributions, with outcomes defined in ways that support statistical analysis and model-based prediction. Scrap is measured as direct material loss in units, weight, or cost normalized by production volume, and it may be decomposed by defect category, station of origin, or material batch (Bridger, 2017). Rework is measured through labor hours, rework routing frequency, queue lengths, and repeated inspection counts, and it can be analyzed as both a capacity consumption variable and a contributor to variability through repeated handling. Downtime is measured through event logs and duration distributions, allowing decomposition into breakdowns, minor stops, changeovers, and planned maintenance. Quality is measured through end-of-line functional tests, dimensional audits, surface appearance grades, torque trace conformance, leak test results, noise-vibration-harshness thresholds, and other standardized inspection outputs. Field quality proxies can be represented through service codes, return rates, and warranty claim frequencies aggregated by component family or production window, creating quantitative links between in-plant variation and downstream outcomes (Tauro et al., 2018). A machine-learning approach treats these outcomes as dependent variables and maps them to predictors derived from process parameters, sensor streams, material identifiers, and operational context. Model development in such a study is framed as a measurable exercise: predictive performance is quantified, error types are tallied, and threshold behavior is analyzed relative to operational costs, such as the waste created by unnecessary rework or the risk created by missed defects. International automotive manufacturing amplifies the significance of these measurable relationships because standardized product platforms require consistent conformance across regions, and supply networks require stable quality performance across diverse supplier and logistics conditions. In this environment, the quantitative emphasis remains on definitional clarity, measurement reliability, and empirical verification of relationships between process data and outcomes. The study domain is characterized through measurable variables, structured datasets, and validated model performance indicators, forming a basis for analyzing how computational learning methods can be applied to reduce quantifiable waste and improve measurable quality within complex automotive production systems (Wiedemann, 2016).

The objective of the study titled Data-Driven Process Optimization in Automotive Manufacturing: A

Machine Learning Approach to Waste Reduction and Quality Improvement was to quantitatively evaluate how integrated manufacturing data and machine learning models had been used to explain and predict measurable waste and quality outcomes within an automotive production environment. The study objective was structured around establishing a clear, measurable connection between station-level process conditions and operational performance indicators by using production-unit traceability across process parameters, equipment condition signals, material batch identifiers, and contextual operating factors. Specifically, the study aimed to operationalize waste reduction through quantifiable outcomes such as scrap occurrence and scrap rate, rework hours per unit, and disruption-linked losses, while operationalizing quality improvement through first-pass yield, defect occurrence probability, and a capability-oriented conformance proxy derived from critical-to-quality measurements and tolerance-based performance. A central objective was to determine whether deviation indicators and stability features extracted from time-indexed sensor and trace data had been statistically associated with increased defect risk, higher scrap likelihood, and increased rework burden after controlling for confounding contextual variables such as product variant, shift, and station family. Another objective was to evaluate the incremental explanatory contribution of equipment condition indicators, including downtime intensity, alarm frequency, and maintenance-recency measures, in predicting waste and quality outcomes beyond what could be explained by process parameters alone. The study also aimed to quantify whether material batch grouping had explained systematic shifts in conformance outcomes and defect probability, thereby capturing upstream variability effects that could not be fully attributed to station settings or equipment state. Methodologically, the objectives included verifying that engineered feature groups were reliable and valid representations of manufacturing mechanisms such as drift, wear, and restart-window instability, and ensuring that predictive relationships were evaluated under dependence-aware validation designs that respected hierarchical clustering and temporal drift typical of high-volume automotive production. Finally, the study aimed to produce a quantitative basis for selecting high-signal predictors and interpretable model structures that supported rigorous hypothesis testing and clear operational interpretation of relationships among process deviation, stability, equipment condition, batch context, and measurable waste and quality performance.

LITERATURE REVIEW

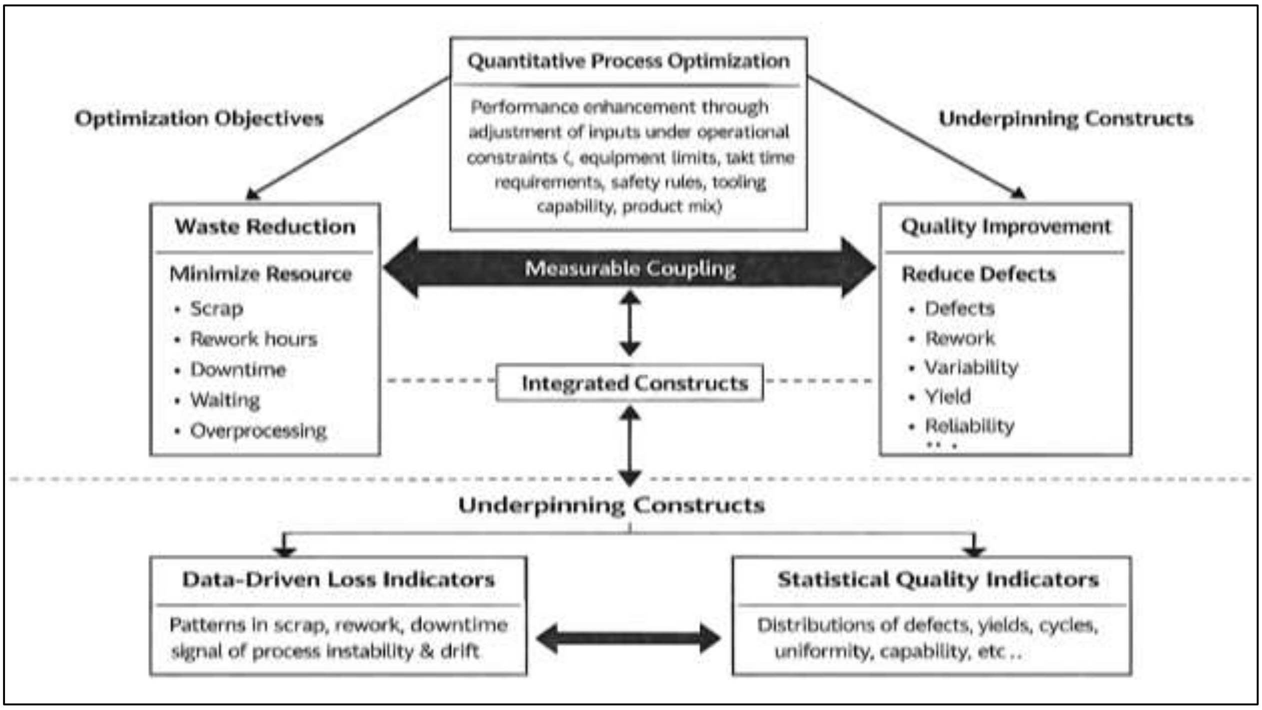
The literature review for this quantitative study synthesizes research streams that explain how data-driven methods and machine learning are used to optimize automotive manufacturing processes with measurable outcomes in waste reduction and quality improvement (Webb et al., 2016). Automotive manufacturing is a high-volume, multi-stage production environment in which small variations in process parameters, material properties, equipment condition, and human actions can propagate across stations and accumulate into scrap, rework, downtime, and nonconformance. Because these outcomes are measurable through production and quality indicators, the literature base relevant to this topic is strongly quantitative and spans quality engineering, lean systems, industrial statistics, manufacturing informatics, and machine learning for industrial applications (Cordes, 2017). This review is organized to establish (a) how waste and quality are defined and quantified in automotive production systems, (b) what data sources and measurement architectures support reliable modeling, (c) which statistical and computational modeling approaches have been used to predict and control defects and waste, and (d) what validation designs and performance metrics are required to claim predictive and operational value in production settings (Fang & Yu, 2017). The section also highlights how modeling choices must align with real manufacturing constraints such as rare defect rates, multistage dependencies, temporal drift, and hierarchical plant structure. By structuring the literature across constructs, data, methods, and evaluation logic, the review builds a coherent foundation for selecting variables, designing the analytic pipeline, and positioning the machine learning approach as a quantitative tool for linking process conditions to measurable waste and quality outcomes in automotive manufacturing (Ko et al., 2019).

Process optimization in discrete automotive manufacturing

Process optimization in discrete automotive manufacturing is most consistently described in the literature as a structured, measurement-based effort to improve process outputs under operational constraints such as equipment limits, takt time requirements, safety rules, tooling capability, and product specification boundaries. In high-volume automotive settings, optimization is treated as a quantitative problem because performance is expressed through observable indicators rather than narrative assessments (Ancillai et al., 2019). Researchers commonly define optimization as the deliberate adjustment of controllable inputs to improve the distribution of outputs, with emphasis on reducing variation, shifting performance toward target values, and stabilizing results across time and product mix. This view aligns with quality engineering traditions that frame manufacturing as a system of variation, where common patterns and assignable disruptions can be detected through disciplined measurement. A critical distinction in manufacturing studies is the level at which optimization is executed. Station-level optimization targets a specific operation or workstation, such as a welding cell, paint booth, machining center, or torque tool, and typically evaluates outputs like dimensional deviation, weld integrity proxies, surface finish, coating uniformity, or torque trace conformance. Line-level optimization emphasizes the interdependence among stations and prioritizes flow stability, queue reduction, balanced cycle times, and the prevention of defect propagation downstream (Sawatzky et al., 2016). Plant-level optimization focuses on aggregated performance across lines and shifts, addressing broader issues such as overall equipment effectiveness, production scheduling stability, systematic maintenance planning, and plant-wide defect containment performance. Quantitative objectives across these levels are typically expressed in terms of minimizing defects, scrap, rework hours, and downtime while maximizing yield, throughput, and process capability. Studies that connect these objectives often emphasize that the "best" setting for a station may not be optimal for the line, because local gains can create downstream constraints, increased buffering, or new failure modes. Similarly, improvements at the line level can be constrained by plant-level considerations such as shared utilities, material supply variability, and workforce allocation. The literature also indicates that optimization in automotive manufacturing requires defining outcomes as distributions rather than single-point results, given that product variants, supplier batches, temperature and humidity fluctuations, and tool wear shift the process state throughout daily operations (Vidal-Ribas et al., 2016). Consequently, quantitative research stresses repeatability and comparability through standardized metrics, consistent sampling logic, and clear operational definitions of performance, enabling results to be evaluated across stations, across lines, and across plants without ambiguity.

Waste in automotive manufacturing is typically operationalized in the literature as measurable resource loss that does not contribute to the product's required function or conformance, and it is broken into categories that can be monitored and analyzed as variables (Yuste et al., 2020). Scrap is the most direct form of measurable waste because it represents material that cannot be converted into a conforming unit; it is often tracked as units scrapped, mass of material lost, or cost per production volume, with further segmentation by defect category, station of origin, product variant, and time window. Rework is treated as a coupled waste-and-quality phenomenon because it reflects both nonconformance and additional consumption of labor and capacity. Quantitative studies commonly express rework as rework hours per unit, rework rate by station, rework routing frequency, and re-entry counts into inspection loops, since repeated handling and repeated verification have measurable impacts on throughput stability and defect risk. Waiting and flow losses are represented through queue time distributions, work-in-process counts, buffer saturation frequencies, changeover durations, and line stop cascades, reflecting how imbalances and instability generate measurable time waste (Shute et al., 2017). Overprocessing is quantified through cycle time excess beyond standard, repeated operations triggered by quality uncertainty, and unnecessary finishing or cleaning steps introduced to compensate for upstream instability. Energy and utility waste are similarly quantified through energy per unit, air consumption per unit, paint or chemical usage per unit, and deviations from standard consumption profiles, particularly in paint shops and thermal processes where deviations are often correlated with quality outcomes and rework activity. Downtime is frequently decomposed into breakdown time, minor stoppages, planned stops, and unplanned interruptions, with attention to frequency, duration, and clustering patterns that reveal the stability of equipment and the effectiveness of maintenance strategies. Across these categories, the literature emphasizes that waste metrics must be normalized by production volume and interpreted in the context of product mix, shift pattern, and equipment age to avoid misleading comparisons. A recurring finding across manufacturing research streams is that waste is not only a cost outcome; it is also a process signal. Patterns in scrap spikes, rework routing surges, queue growth, and downtime clustering frequently coincide with drift in process parameters, tool wear progression, material batch changes, and environmental variation (Sarkar & Searcy, 2016). For this reason, the literature positions waste variables as central dependent measures in quantitative optimization studies and as diagnostic indicators that reveal where and when process instability is converting variation into measurable loss.

Figure 3: Quantitative Automotive Process Optimization Framework



Quality improvement in automotive manufacturing is defined in the literature as the measurable enhancement of conformance and consistency, achieved through reducing defect incidence, tightening output distributions, and increasing the stability of production outcomes across time and variants (McGarigal et al., 2016). Conformance metrics are commonly operationalized through defect rates normalized at scale, such as defects per unit, parts-per-million nonconformance, defect density by subsystem, and audit-based scoring systems that reflect adherence to dimensional and functional requirements. Many studies emphasize that audit scores and defect counts should be interpreted alongside measurement system reliability, because inconsistent inspection sensitivity or shifting defect taxonomies can distort observed trends. Capability-oriented perspectives define quality improvement as increased capability relative to specifications, operationalized through capability indices and sigma-level proxies that summarize how often outputs fall within tolerance. In automotive environments with complex assemblies and many interacting tolerances, first-pass yield is repeatedly highlighted as a practical and highly informative metric because it captures the proportion of units that pass a defined quality gate without rework. Rolled throughput yield extends this concept across multiple stages and is used to quantify how defects accumulate through the process chain, offering a system-level view of quality performance. End-of-line testing contributes additional measurable outputs, including pass/fail outcomes, threshold exceedances, diagnostic code frequencies, leak test results, functional calibration results, and other standardized checks that capture final conformance (Ribeiro & Barbosa-Povoa, 2018). The literature also incorporates downstream proxies such as warranty claims, return rates, service codes, and customer complaint classifications aggregated by production period, product family, or supplier batch, as these provide measurable evidence of field quality performance. Studies synthesizing these indicators often stress that quality improvement is multi-dimensional: defect prevention, detection effectiveness, containment performance, and the stability of the measurement process itself all contribute to observed results. A key quantitative insight recurring across research is that quality improvement is best described through distributional change: reductions in variance, reduction in tail risk where out-of-spec values cluster, improved stability over time, and fewer abrupt shifts associated with assignable causes. Because automotive manufacturing is characterized by high volume, tight tolerances, and regulatory and safety expectations, quality metrics are rarely treated as optional or secondary; they are treated as core performance variables that interact with productivity measures (Jiang et al., 2019). As a result, research frameworks commonly evaluate quality improvement alongside throughput, downtime, and rework measures, showing that quality changes have measurable consequences for line stability, capacity utilization, and overall cost structure, even when the immediate focus is on conformance outcomes.

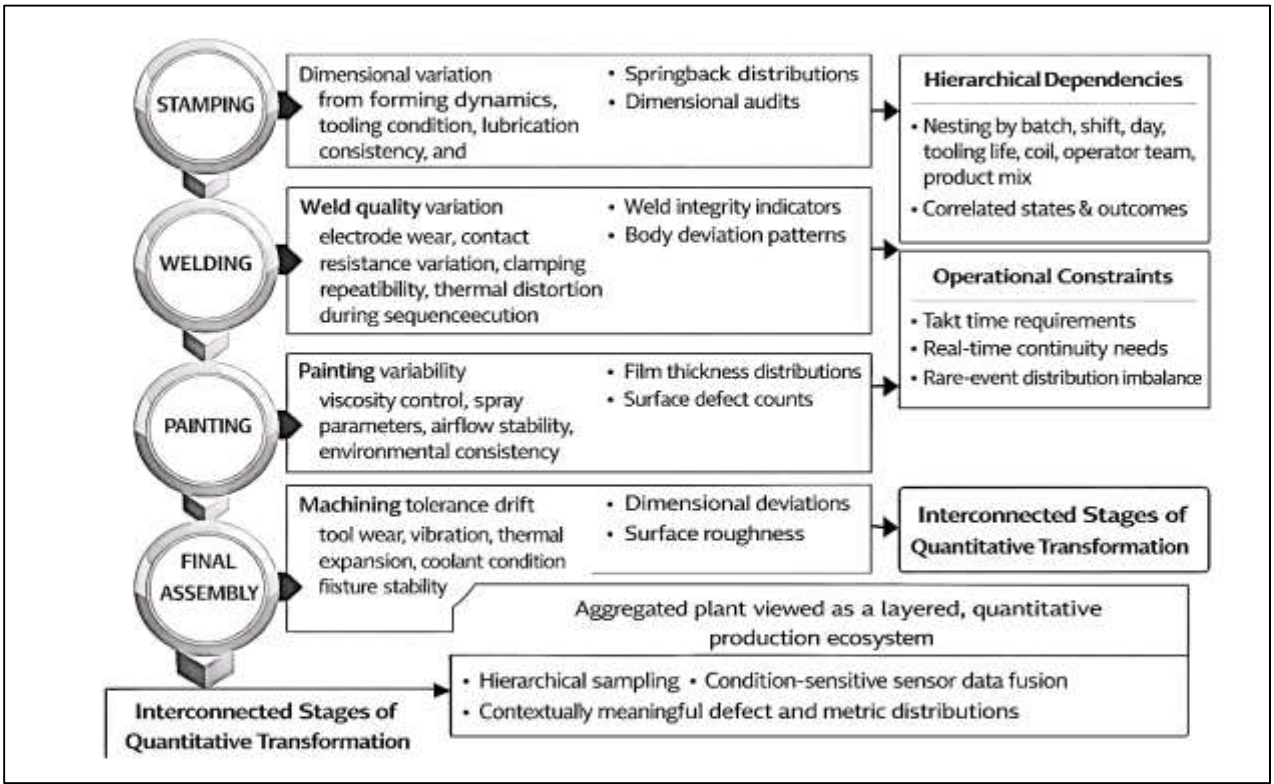
The relationship between waste and quality is consistently treated in the literature as a measurable coupling rather than separate domains, because the same process mechanisms that generate nonconformance also generate resource loss through scrap, rework, downtime, and flow disruption (Sas-Chen et al., 2020). Rework loops are a primary example of this coupling: when a unit fails inspection and is routed back for correction, quality risk increases due to additional handling, repeated tool engagement, and potential introduction of secondary defects, while waste increases through added labor time, increased queueing, and re-inspection load. Quantitative studies often observe that increased rework activity changes the effective process conditions by creating bottlenecks and shifting work content, which can further alter defect probabilities in downstream stations. Process drift is another mechanism repeatedly linked to both waste and quality outcomes. As tools wear, fixtures loosen, sensors drift, or environmental conditions shift, output distributions can gradually move away from targets, increasing the likelihood of out-of-spec results. This drift manifests simultaneously as higher scrap and higher defect probability, and it often appears as gradual trends in measurement data followed by sudden spikes when thresholds are crossed or when compensating actions become insufficient. Multistage propagation is central in automotive assembly because deviations in upstream operations can constrain downstream fit, alignment, and functional performance (Weimer & Vining, 2017). A small dimensional deviation from stamping can increase variation in body assembly, which then affects closure fit, seal integrity, paint appearance, and final noise or leak outcomes. This propagation increases both the frequency of quality failures and the operational waste associated with containment actions, such as additional inspections, manual adjustments, part sorting, and line stoppages to prevent escape. The literature also highlights that waste metrics can act as early indicators of quality degradation: rising queue times, increased minor stoppages, and growing rework routing frequency often precede visible spikes in end-of-line defects. Conversely, changes in inspection rigor can alter recorded quality metrics while simultaneously increasing waste through over-inspection and unnecessary rework, indicating that measurement practices themselves influence observed coupling. For quantitative optimization research, this coupling implies that dependent variables should be selected and interpreted jointly. Scrap, rework hours, first-pass yield, and downtime are interrelated outcomes tied to a shared set of process drivers. Studies commonly recommend modeling frameworks that account for shared variance among these outcomes and that recognize hierarchical dependence across shifts, batches, and lines (Jack & Thompson, 2017). Overall, the literature frames the waste–quality relationship as an empirically observable system dynamic in which process variation and instability are converted into both nonconformance and resource loss, making combined measurement and integrated analysis central to any data-driven optimization effort in automotive manufacturing.

Automotive Manufacturing Context

Automotive manufacturing is widely represented in the literature as a quantitative production system because each stage transforms inputs into outputs that can be measured as distributions rather than single values (Katchasuwanmanee et al., 2017). Stamping operations illustrate this logic clearly: sheet metal behavior introduces dimensional variation through forming dynamics, tooling condition, lubrication consistency, and material property differences across coils. Springback is treated as a measurable phenomenon because the part's geometry changes after forming forces are removed, producing deviations that appear in coordinate measurement records, gauge readings, and dimensional audit reports. Researchers describe stamping quality as a function of both controllable settings and inherent material variability, which is why dimensional conformance is often analyzed across batches and time windows rather than as isolated events. In body-in-white welding, defect formation mechanisms include inconsistency in weld nugget formation, electrode wear, contact resistance variation, clamping repeatability, and thermal distortion during sequence execution. These mechanisms generate measurable outcomes such as weld integrity indicators, dimensional body measurements, gap-and-flush results, and audit-derived deviation patterns, which are treated as quantitative outputs that shift with equipment state and process conditions (Sabbagh et al., 2017). Paint operations are similarly described as data-rich because film build thickness, surface appearance, and defect counts can be monitored through inline sensors, inspection images, and standardized defect classification systems. Variability in paint thickness and surface finish arises from changes in viscosity control, spray parameters, booth airflow stability, environmental conditions, and curing profiles, leading to measurable distributions in film build and counts of surface defects such as runs, inclusions, or texture inconsistencies. Machining stages introduce another form of measurable variation through tool wear progression, vibration, thermal growth, coolant condition, and fixturing stability, which appear as patterns in surface roughness measurements, dimensional tolerance drift, and inspection failures. Final assembly converts upstream variation into functional outcomes: torque trace conformance, leak test outputs, and functional checks create quantitative signals that capture whether assembled systems meet defined performance thresholds (Omair et al., 2019). Across these stages, the literature treats defect formation as multicausal and measurable, requiring datasets that preserve station identity, time ordering, product variant context, and inspection results. The plant is therefore modeled as a sequence of measurable transformations in which each stage produces process signatures and output distributions that reflect both controllable conditions and structural sources of variation (Zimmer et al., 2017).

High-volume automotive environments impose constraints that shape how quantitative modeling is conducted, and the literature consistently emphasizes that these constraints alter both the structure of available data and the interpretation of results. Takt time requirements constrain intervention opportunities because stations operate within fixed cycle windows and changes to settings, inspection routines, or rework routing influence throughput stability (Elverum & Welo, 2016). As a result, modeling approaches are often described as needing to respect production continuity, meaning that data collection and analysis methods align with what is feasible in real-time operations rather than laboratory-like experimentation. Another prominent constraint is the rare-event structure of many critical defects. Even when overall defect rates remain low, certain failure modes carry high cost due to safety, warranty exposure, or downstream rework cascades. This creates an imbalance in outcome distributions, where the majority of units pass inspection and a small number fail, which affects the reliability of naïve accuracy measures and requires careful attention to how performance is assessed. Product mix and variant complexity further complicate modeling because a single line may build multiple configurations with different parts, options, and assembly sequences. In the literature, product variant indicators are treated as essential categorical predictors that influence both baseline defect probabilities and the relevance of specific process parameters (Hermann et al., 2016). Batch and shift effects also appear repeatedly because production behavior changes with material lots, tool life stages, staffing composition, and environmental cycles across the day. These effects show up in distributions of dimensional measures, defect counts, downtime events, and torque or test signatures, which means models that ignore batch and shift structure risk confusing normal contextual variation with true process anomalies. High-volume production also generates strong autocorrelation in time because consecutive units share similar conditions, so the assumption of independent observations is frequently challenged. Studies describe the need to align data windows with operational realities such as changeovers, maintenance intervals, coil changes, or inspection regime shifts. Under these conditions, data-driven optimization is presented not as a purely computational exercise but as a measurement and modeling practice embedded in operational constraints, where the meaning of “improvement” is evaluated using metrics that remain stable across product variants, batches, and shifts while still capturing the signals associated with defect formation and waste (Schöggl et al., 2017).

Figure 4: Automotive Manufacturing Quantitative Measurement Framework



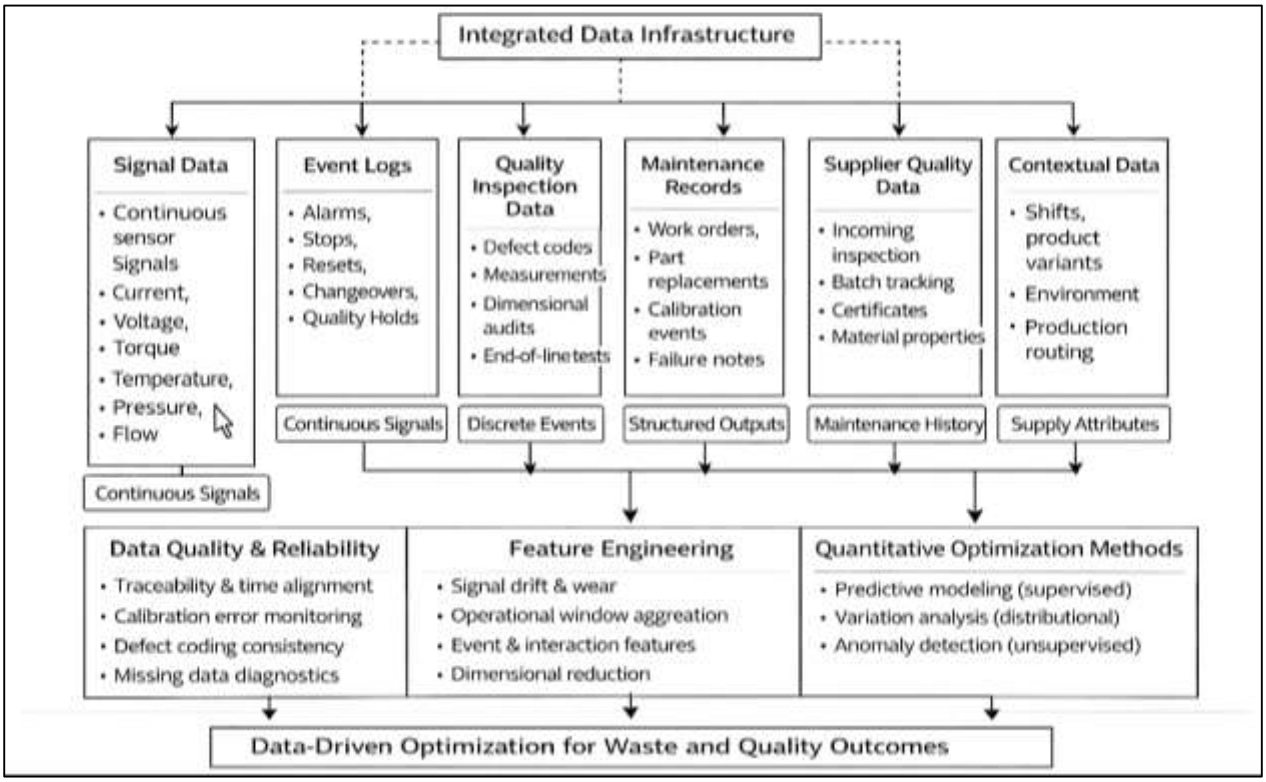
The literature also treats automotive manufacturing as a hierarchical and dependent system in which observations are nested and correlated across multiple organizational layers, shaping how quantitative sampling and validation are designed. Parts are produced within batches, batches occur within shifts, shifts operate on lines, and lines exist within plants, creating structured dependence because units produced close together share equipment states, tool wear conditions, operator teams, and material sources (Patala et al., 2016). Shared tooling is a common dependency source: a stamping die, welding electrode set, paint applicator, or machining tool influences many consecutive units, so measurement patterns cluster by tool life segment. Shared materials introduce another dependency layer through coil identity, resin batch, paint lot, adhesive batch, or fastener supplier lot, which affect conformance distributions and defect tendencies in ways that persist across time windows. Shared operators and teams add correlated human-system interactions through work practice consistency, response to minor stoppages, and adherence to standardized work, which are represented in the literature as contextual variables that shift distributions rather than random noise. Because of these dependencies, research discussions emphasize that splitting data randomly can cause leakage, where records with nearly identical process signatures appear in both training and testing samples, inflating apparent model performance (Costa et al., 2017). Sampling logic is therefore treated as a methodological priority, with many studies describing grouped or time-ordered splitting strategies that preserve realistic generalization requirements. Hierarchical structure also influences interpretability: a predictor that appears important at the part level may actually reflect a line-level condition such as a drifting sensor, a maintenance state, or a product mix shift. Quantitative reviews stress that analysis must distinguish between within-group variation and between-group variation to avoid attributing plant-level effects to part-level factors. This hierarchical view is especially relevant in multi-plant settings, where the same platform is produced across facilities with different equipment ages, supplier portfolios, and environmental conditions. Under such circumstances, the literature presents generalization as a measurable question: whether a model trained under one line's distribution maintains performance under another line's distribution. The resulting methodological emphasis is on preserving the nested structure of the data in both descriptive statistics and model validation, ensuring that findings reflect true relationships between process conditions and outcomes rather than artifacts of correlated sampling (Shalender & Yadav, 2019). Automotive manufacturing is therefore represented as a quantitative

system not only because it produces abundant measurements, but also because the statistical structure of those measurements is inherently dependent and layered.
Across the reviewed research streams, the automotive plant is positioned as an interconnected measurement ecosystem where stage-level signals, operational constraints, and hierarchical dependencies jointly determine the quality of any quantitative analysis (Spada et al., 2017). Each process stage contributes a distinct type of data: stamping provides geometry-focused measures sensitive to material behavior and tool condition; body-in-white welding contributes strength and dimensional indicators shaped by electrical, mechanical, and thermal stability; paint adds thickness distributions and defect counts influenced by chemistry, airflow, and curing; machining produces drift-sensitive tolerance and surface measurements tied to tool wear and thermal effects; final assembly generates functional conformance data such as torque traces, leak results, and end-of-line checks that reflect both upstream variation and assembly execution. The literature treats the interactions among these stages as central because upstream deviations alter downstream process conditions and raise the probability of nonconformance in later checks, creating linked patterns of variation that appear across multiple datasets. High-volume constraints intensify this coupling: when takt time pressure increases, minor stoppages and recovery actions change station rhythms, rework routing expands, and inspection intensity may shift, all of which produce measurable changes in distributions. Rare defects create additional complexity because the most consequential failures occur infrequently but are associated with identifiable precursors in process signatures, leading studies to emphasize the importance of sensitivity to subtle changes in multivariate patterns (Colledani et al., 2018). Product variants and batch identities act as essential context that shapes baseline distributions, meaning that the same sensor pattern can have different meaning under different variants or material lots. Hierarchical dependence further shapes interpretation by concentrating variation within shared tooling and shared material windows, so that a drift episode can manifest as a cluster of dimensional deviations, a spike in rework routing, and a rise in end-of-line failures within a single shift or batch segment. Methodologically, this integrated view leads the literature to emphasize careful dataset construction, explicit station and time indexing, and validation strategies that respect grouping and time dependence. The plant is therefore analyzed as a quantitative system defined by measured outputs, constrained decision opportunities, and structured dependence, where credible insights depend on aligning modeling designs with production realities. This framing supports a literature-based understanding of automotive manufacturing as a domain in which measurement richness is inseparable from measurement structure, and where the quality of conclusions depends on preserving the operational and hierarchical context that generates the observed waste and quality outcomes (Hietanen et al., 2020).

Data Infrastructure for Data-Driven Optimization

Industrial data infrastructure is presented in the literature as the backbone of data-driven optimization because it determines what can be measured, how reliably it can be compared across time and stations, and whether analysis results reflect process reality rather than recording artifacts. Automotive manufacturing environments generate heterogeneous data streams that represent different layers of process behavior (Zheng et al., 2016). Continuous sensor signals capture physical dynamics and equipment states at high frequency, including electrical and mechanical signatures such as current, voltage, vibration, torque, temperature, pressure, and flow. These signals are typically treated as time-indexed variables that reflect both immediate control actions and gradual wear patterns. Discrete event logs complement sensor streams by recording operational transitions and disruptions, such as alarms, stops, resets, changeovers, and quality holds, which create interpretable markers for when the process state changed. Structured quality inspection data serve as the primary output layer of the production system, including defect codes, measurement results, dimensional audit outcomes, and end-of-line test results. Because these data often serve as labels for predictive modeling, the literature treats their definitions and consistency as central to analysis credibility. Maintenance records add another critical domain by providing work orders, preventive schedules, repair histories, parts replacements, lubrication actions, calibration events, and failure mode notes, which can be aligned with shifts in scrap, rework, or defect rates (Tripathi & De, 2019). Supplier quality data extend the system boundary upstream through incoming inspection results, certificates, batch identifiers, and material property descriptors, supporting the idea that variation often originates before parts reach the line. Context data tie all of these streams to the operational environment by encoding shift, crew, product variant, station identifier, environmental conditions, and production routing information. Literature across manufacturing informatics, quality analytics, and operations research repeatedly emphasizes that these variable types cannot be treated as interchangeable: sensor streams describe continuous dynamics, event logs describe discrete transitions, quality records describe outcomes and classifications, maintenance logs describe interventions and degradation pathways, supplier datasets describe upstream variation, and context variables describe confounding structure (Jin et al., 2018). Data-driven optimization becomes feasible when these sources are integrated into coherent datasets that preserve station identity, time ordering, and product lineage, allowing waste and quality outcomes to be quantitatively linked to process conditions across the full manufacturing system.

Figure 5: Industrial Data Infrastructure Optimization Framework



Data quality and measurement reliability are consistently treated as limiting conditions in industrial analytics because modeling accuracy and interpretability depend on whether recorded signals represent the true process state. The literature frequently highlights measurement error in sensors, drift in calibration, and variability in sampling practices as sources of biased or unstable relationships. In automotive settings, sensors can experience gradual drift due to temperature changes, mechanical looseness, or aging electronics, which alters signal baselines and can mimic process change if not accounted for (Hewitt & Frejinger, 2020). Label noise is another dominant theme, particularly in defect coding and inspection outcomes. Defect codes may vary by inspector judgment, inspection station sensitivity, lighting and viewing conditions, or changing defect taxonomies, resulting in inconsistent labels that reduce the reliability of supervised learning tasks. Missing data patterns are also described as structurally meaningful rather than random. Missingness can occur when sensors fail, communication links drop, stations bypass certain checks due to downtime recovery, or inspection intensity changes by shift, meaning that gaps in data often correlate with operational disturbances. Sampling frequency differences across stations create further complications: some stations record high-frequency traces, others record summary values per unit, and others only log exceptions, which results in datasets with uneven resolution across the process chain (Bertsimas et al., 2018). Data synchronization across industrial systems is repeatedly emphasized as a central reliability challenge because process variables and outcomes often live in separate systems. PLC data may record raw signals and timestamps, MES may record unit genealogy and routing, SCADA may record supervisory monitoring events, and QMS may record inspection results and defect codes. When timestamps are not aligned or when unit identifiers are inconsistent across systems, the linkage between predictors and outcomes becomes uncertain, producing mis-joins that inflate noise and distort relationships. The literature also notes that changes in data collection practices, software upgrades, inspection rule modifications, and sensor replacements create regime changes that must be documented and accounted for in analysis (Kellerer et al., 2019). In this view, data quality is not a preprocessing afterthought; it is an integral part of manufacturing measurement science, requiring explicit attention to reliability, traceability, and consistency so that models built for waste reduction and quality improvement are based on stable, verifiable representations of the production system.

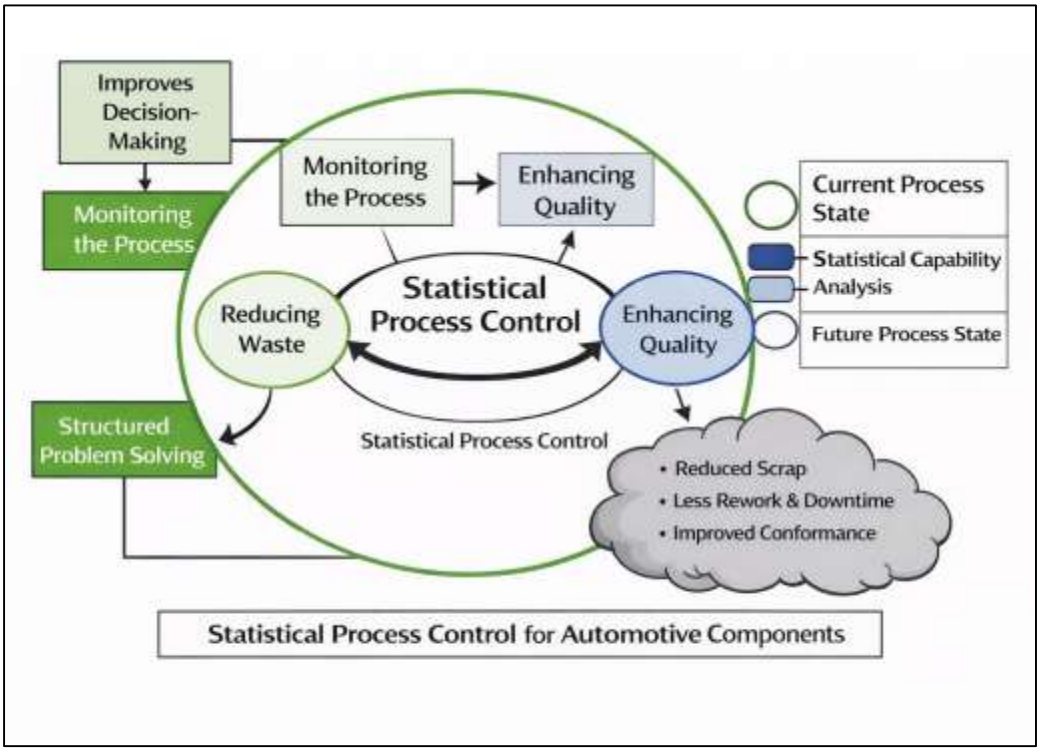
Feature engineering is described in the literature as the bridge between raw industrial data and meaningful predictors that reflect manufacturing physics and operational logic. Raw sensor values often capture noise, transient spikes, and control oscillations that do not directly represent the underlying state relevant to defect formation, so studies emphasize transforming signals into features aligned with how processes degrade, drift, and transition (Haile et al., 2020). Drift and wear are frequently represented using lag-based constructs that summarize how a signal behaves across recent production history, capturing gradual changes associated with tool wear, thermal stabilization, contamination buildup, or electrode degradation. Temporal summarization is also tied to operational windows: features are often aggregated over batches, shifts, changeover segments, or tool life intervals to align measurement with causal mechanisms that unfold over those time scales. Derived stability features are described as particularly useful because they translate a complex waveform into interpretable indicators of process consistency, such as variability bursts, sudden instability, or sustained deviation from typical behavior. Operational transitions are also engineered into features using event logs, where stops, alarms, resets, and changeovers mark state boundaries that separate stable production from transitional or recovery modes. Interaction features appear frequently in manufacturing studies because many defects arise from combined conditions rather than isolated variables. Tool age combined with material batch identity can explain variation that neither factor explains alone, and environmental conditions combined with cure time or paint viscosity can explain surface defects more effectively than either variable independently (Tao et al., 2018). Because sensor spaces are often highly correlated, dimensional reduction methods are described as useful for capturing the dominant modes of variation without treating each sensor channel as independent. This is especially relevant in welding, machining, and paint operations where multiple correlated signals change together as the process state shifts. Across the literature, the guiding principle is that engineered features should preserve physical meaning, support repeatable computation, and remain robust under realistic noise and missingness conditions. Feature engineering is therefore framed as a quantitative modeling decision that directly affects interpretability and generalization, with emphasis on creating predictors that represent stable process states, degradation pathways, and operational regimes that plausibly precede measurable outcomes like scrap, rework, defects, and end-of-line failures (Yang et al., 2017).

Methods Used for Waste and Quality Improvement

Statistical process control is consistently presented in the literature as the foundational quantitative monitoring approach for waste reduction and quality improvement in high-volume manufacturing because it converts streams of production and inspection measurements into structured evidence about stability, change, and assignable disruption (Ali et al., 2019). In automotive environments, where processes run continuously and outputs are produced in large quantities, the central premise is that variation is always present and must be separated into stable variation patterns and non-routine disturbances that demand corrective action. Control charts are used as the baseline tool for this purpose because they enable ongoing interpretation of measurements such as dimensional readings, torque values, weld current stability indicators, coating thickness, or functional test results as time-ordered sequences. The literature emphasizes that the value of chart-based monitoring is not limited to "flagging" a point; it is also used to detect sustained patterns, clustering, and gradual drift that indicate an underlying shift in the process state. Multivariate monitoring is discussed as an extension required by modern automotive production, where many sensor channels move together and a defect mechanism is often reflected in correlated changes across signals rather than a single variable (Fercoq et al., 2016). Capability analysis is also framed as central to quantitative improvement because it translates the distribution of measured outputs into a conformance interpretation: how well the process fits within specification boundaries under routine conditions. This capability perspective provides a measurement-based way to compare stations, track changes after interventions, and prioritize improvement effort where conformance risk is concentrated. The literature also links SPC practices directly to waste outcomes, since unstable processes increase scrap, rework, and downtime through repeated stops, inspection holds, and corrective adjustments. Another recurring theme is special-cause identification logic: once a non-routine signal is detected, the monitoring system supports structured investigation by time-stamping the onset of change and narrowing likely causes to equipment events, material batch changes, operator transitions, or maintenance actions. In production settings, this logic is treated as a disciplined alternative to reactive troubleshooting, allowing teams to use measurement histories and event logs to distinguish meaningful signals from noise (Kamarehie et al., 2020). Researchers also describe the limits of SPC when measurement systems are unreliable or when inspection practices change, because unstable measurement produces false signals and masks true drift. For this reason, many works situate SPC within a broader measurement discipline that includes consistent defect coding, stable sampling rules, and traceable instrument calibration. Overall, traditional monitoring research frames SPC as the quantitative "starting point" for waste and quality improvement because it provides a shared language of stability, variation, and detectable change that supports comparability across shifts, lines, and plants.

Design of experiments is treated in the literature as the core traditional method for establishing measurable cause-and-effect relationships between controllable factors and quality or waste outcomes, especially when the production environment contains complex interactions that observational analysis cannot separate with sufficient confidence (Van Der Aalst et al., 2016). In discrete automotive manufacturing, controllable factors can include process settings, sequence parameters, fixture conditions, curing times, feed rates, clamping forces, or inspection thresholds, while outcomes include defect counts, dimensional deviations, surface appearance grades, scrap volume, or rework routing frequency. Experimental designs are described as structured plans for varying factors in a deliberate way so that the resulting changes in outcomes can be attributed to those factors with quantified effect sizes rather than assumed associations. The literature distinguishes screening designs from more comprehensive designs. Screening approaches are used when there are many potential factors and limited production opportunity, allowing teams to identify the few factors with the largest measurable influence on the response. More comprehensive designs are described as appropriate when the set of influential factors is smaller and when interactions among factors are expected to be important, such as cases where a setting has different effects depending on tool wear stage, material batch, or environmental condition (Garza-Reyes et al., 2018). Interaction modeling is repeatedly emphasized because many automotive defect mechanisms are not additive; they emerge when conditions coincide, such as a marginal parameter setting becoming problematic only under a specific supplier batch or humidity range. Response optimization traditions in experimentation literature describe how results can be used to tune parameters toward stable operating regions where outputs show reduced variability and improved conformance consistency. In operational terms, the intent is to identify settings that reduce scrap and rework and increase first-pass yield while respecting constraints such as cycle time, equipment limits, and safety rules. A recurring finding is that experimental validity in production is constrained by real-world limitations: takt time pressure, limited willingness to interrupt production, restrictions on altering safety-critical settings, and the need to maintain product conformance throughout the study period (Rejeski et al., 2018). The literature addresses these constraints by discussing practical design strategies such as conducting experiments during planned trials, changeovers, or controlled production windows; using blocking logic to separate shift or batch effects; and combining designed variation with tight monitoring to prevent defect escape. Another common discussion point is that experiments require high measurement reliability; if the response measurement is noisy or inconsistent, estimated effects become unstable and conclusions become difficult to reproduce. For that reason, many sources position experimental methods as inseparable from measurement system discipline and careful definition of response variables. In sum, the experimental literature depicts design of experiments as the traditional quantitative pathway for moving from detection of problems to verified identification of controllable causes, expressed through measured effect magnitudes and reproducible improvement evidence (Mizuno, 2020).

Figure 6: Statistical Process Control Framework



Lean and Six Sigma frameworks are discussed in the literature as integrated measurement-centered systems that organize waste and quality improvement around structured cycles and standardized indicators, bridging engineering measurement with managerial execution. Lean traditions emphasize waste identification and flow stability, using quantifiable indicators such as cycle time, queue time, work-in-process levels, changeover duration, line balance losses, and rework routing frequency to make non–value-adding consumption visible in numerical terms (Gálvez-Martos et al., 2018). Six Sigma traditions emphasize defect reduction and variability control, framing improvement as a measurable reduction in nonconformance and process variation while improving consistency against specification targets. The literature often presents these frameworks as complementary: lean focuses on flow and waste categories that degrade throughput and efficiency, while Six Sigma provides statistical rigor for verifying that observed changes represent real improvement rather than random fluctuation. The DMAIC cycle is frequently described as the organizing structure that converts improvement intent into measurable execution. In the Define stage, the problem is translated into clear outcome variables such as scrap rate, rework hours, first-pass yield, or downtime minutes. In the Measure stage, attention is given to measurement reliability, defect code consistency, sampling logic, and baseline characterization of distributions. In the Analyze stage, the focus is on identifying patterns and drivers using quantitative reasoning, which may include comparative analyses across shifts, stations, batches, and product variants, as well as structured root-cause investigation supported by data. In the Improve stage, changes are implemented in a controlled manner and evaluated against defined indicators, and in the Control stage, monitoring structures are put in place so that performance remains stable and deviations are detected early (McAdam et al., 2019). A repeated theme in the literature is that "mapping waste" becomes operational only when waste categories are tied to measurable variables and tracked consistently over time. For example, waiting waste is quantified through queue distributions and stop durations, transport and motion are approximated using handling counts and route distances when available, and overprocessing is reflected in cycle time excess and repeated operations linked to quality uncertainty. Another recurring emphasis is linkage between measurement systems and verified performance changes; improvement claims are treated as credible when measurement definitions remain stable and when changes are observed across multiple indicators rather than a single metric that can be influenced by reporting practices. The literature also notes that these frameworks rely on cross-functional participation and standardization because many waste and defect mechanisms cross station boundaries, connecting upstream variation to downstream rework and final inspection outcomes (Ding, 2018). Overall, lean and Six Sigma research portrays these systems as traditional quantitative infrastructures for improvement because they formalize the selection of metrics, the discipline of measurement, the structure of analysis, and the verification of change in a repeatable, comparable way across automotive production contexts.

Maintenance analytics and equipment effectiveness are treated in the literature as essential traditional quantitative approaches because equipment condition is a primary driver of both waste and quality variation in high-volume automotive manufacturing. Equipment effectiveness is often represented as a structured view of loss, separating production losses into categories such as availability-related downtime, performance-related speed losses, and quality-related yield losses (Dixon-Woods & Martin, 2016). This decomposition is emphasized because it creates a measurable taxonomy for understanding how equipment behavior translates into waste pathways: breakdowns and micro-stops create waiting and throughput losses, speed losses reduce capacity and disrupt flow, and quality losses appear as scrap and rework that consume material and labor. The literature repeatedly stresses that downtime must be treated as a distribution rather than a single number because failure behavior often clusters by time, shift, product mix, and maintenance history. Patterns in downtime frequency and duration provide measurable signals about equipment degradation pathways, maintenance effectiveness, and operational stress. Maintenance records are described as a valuable quantitative source because they document interventions, component replacements, lubrication events, calibrations, and failure modes that can be aligned with shifts in quality outcomes such as defect rates, dimensional drift, and scrap spikes. Traditional predictive maintenance discussions emphasize condition indicators derived from measurements such as vibration levels, temperature drift, current signatures, and cycle anomalies, treating these as predictors that correlate with imminent failures or quality deterioration (Pereira et al., 2019). A central point across the literature is that equipment problems do not only produce downtime; they also degrade process capability while the machine is still running, creating subtle variation increases that later manifest in rework, scrap, and end-of-line failures. For that reason, many sources discuss integrating maintenance variables into quality improvement analysis, such as linking tool life stage, calibration status, or repair history to defect distributions and process instability. Another recurring theme is the distinction between planned and unplanned downtime, since planned maintenance can stabilize processes when scheduled effectively, while unplanned failures introduce disruption that increases waste and raises quality risk through rushed recovery actions and inconsistent restarts. The literature also addresses the operational reality that maintenance priorities are influenced by production pressure, meaning that equipment condition and intervention timing can vary systematically by shift, product demand, or line criticality (Morgan & Liker, 2020). This systematic variation becomes important for quantitative analysis because it shapes observed relationships between maintenance events, downtime patterns, and quality outcomes. Overall, traditional maintenance analytics research positions equipment effectiveness measurement and condition-based indicators as central tools for waste and quality improvement because they provide measurable pathways connecting equipment behavior to scrap, rework, throughput instability, and conformance variability within automotive production systems (Abdel-Shafy & Mansour, 2018).

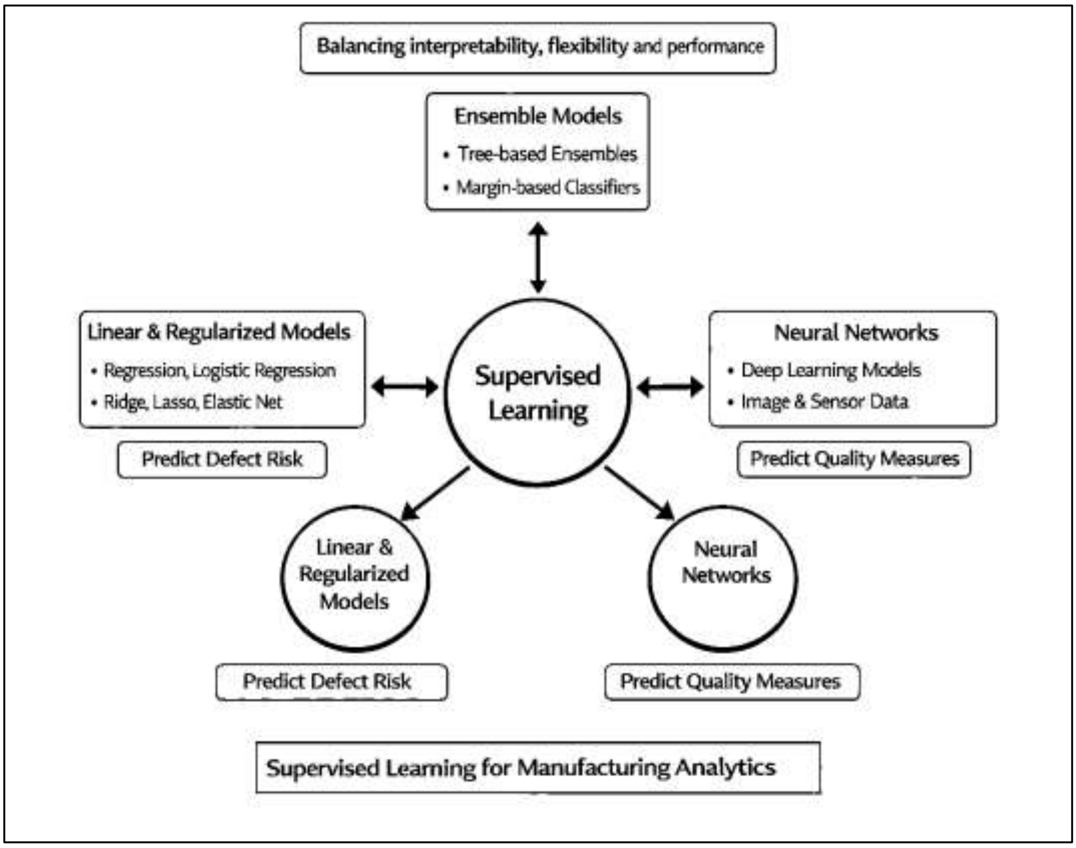
Machine Learning for Automotive Process Optimization

Supervised learning is widely discussed in the manufacturing analytics literature as a practical approach for converting historical production records into predictive models that estimate defect risk and classify quality outcomes at scale (Weichert et al., 2019). In automotive production, supervised learning typically assumes that quality outcomes are observable and recorded in structured form, such as pass/fail inspection results, defect codes, dimensional measurements, torque trace status, or end-of-line functional test outcomes. Binary defect risk modeling is commonly positioned as the simplest operational formulation, where the goal is to distinguish units likely to be nonconforming from those

likely to pass, using predictors such as process setpoints, sensor summaries, station identifiers, material batches, and maintenance context. Studies frequently note that the binary framing aligns well with inspection gates and containment decisions, since many operational actions depend on whether a unit should be routed for rework or released. Multi-class defect type classification extends this approach by predicting the specific defect category, which supports targeted troubleshooting because different defect classes are associated with different physical mechanisms, stations of origin, and corrective actions (Peres et al., 2019). Research discussions emphasize that the quality of multi-class classification depends on defect taxonomy consistency and labeling reliability, because ambiguous or inconsistent defect coding weakens the learning signal and can collapse distinct mechanisms into noisy categories. Regression-based supervised learning is often described as essential when quality outcomes are continuous rather than categorical, such as dimensional deviation from target, coating thickness variation, surface roughness levels, or leak-rate magnitudes. In these settings, the objective becomes predicting the magnitude and direction of deviation, allowing analysts to characterize drift patterns and identify process conditions associated with widening variability (Gstalter et al., 2020). Across these supervised tasks, the literature repeatedly stresses that modeling is meaningful only when linked to realistic data structures, including time ordering, product variant context, and station-level segmentation. It also emphasizes that manufacturing data are not static: tool wear, maintenance interventions, environmental shifts, and supplier variation reshape relationships between predictors and outcomes, which means supervised models are often evaluated for stability across shifts, batches, and operating regimes. Overall, supervised learning is portrayed as a measurable approach to transforming production data into quantitative predictors of defects and quality states, with the strongest studies grounding model formulation in the specific decision points and measurable outcomes that exist in automotive quality systems (Syafrudin et al., 2018).
Model families used in automotive manufacturing analytics are discussed in the literature in terms of a trade-off between interpretability, flexibility, and suitability for the structure of industrial data. Linear and regularized models are often treated as interpretable baselines because they express relationships in a way that supports engineering reasoning, enabling teams to identify which factors are associated with rising defect risk or deviation magnitude (Luckow et al., 2016). Regularization is emphasized because manufacturing datasets frequently contain many correlated predictors, including multiple sensor channels and related process settings, and models that control complexity can remain stable when predictors overlap. Tree-based ensembles are commonly presented as strong performers in industrial contexts because they capture non-linear interactions among variables without requiring manual specification of interaction terms. This is repeatedly described as valuable in automotive processes where defects can emerge only when conditions coincide, such as a particular parameter setting becoming problematic under a specific material batch or tool life stage (Dargan et al., 2020). Margin-based classifiers such as support vector machines are often positioned as effective when class boundaries are complex and when the objective is robust separation between conforming and nonconforming observations in high-dimensional predictor spaces. Neural networks are discussed as particularly relevant when the mapping between predictors and outcomes is highly non-linear or when inputs are unstructured, such as images from surface inspection, acoustic signatures, or waveform-like sensor traces. In automotive quality control, image-based inspection is frequently treated as a natural application area because many defects are visual, and inspection systems increasingly produce large sets of labeled images. Sequence models are highlighted in research streams focused on time-dependent sensor data, where the process state evolves and where defect formation is linked to temporal patterns rather than single snapshots (Yan & Xu, 2018). This includes situations where gradual drift, warm-up behavior, or tool wear progression alters signals over many cycles before a defect appears. Across model families, the literature tends to emphasize that manufacturing modeling is constrained by operational realities: models must tolerate noise, missingness, and differences in sampling frequency across stations, and they must remain reliable under product mix shifts and shift-level variability. Many studies also point out that model selection is inseparable from evaluation design, because a model that performs well under random splitting can perform poorly under time-ordered or group-based validation when dependence and drift are respected. In summary, the literature frames model families as a toolkit whose suitability depends on the data modality, the need for interpretability, the degree of

non-linearity, and the temporal structure of the process, rather than as a single "best" choice for all automotive manufacturing problems (Xu et al., 2019).

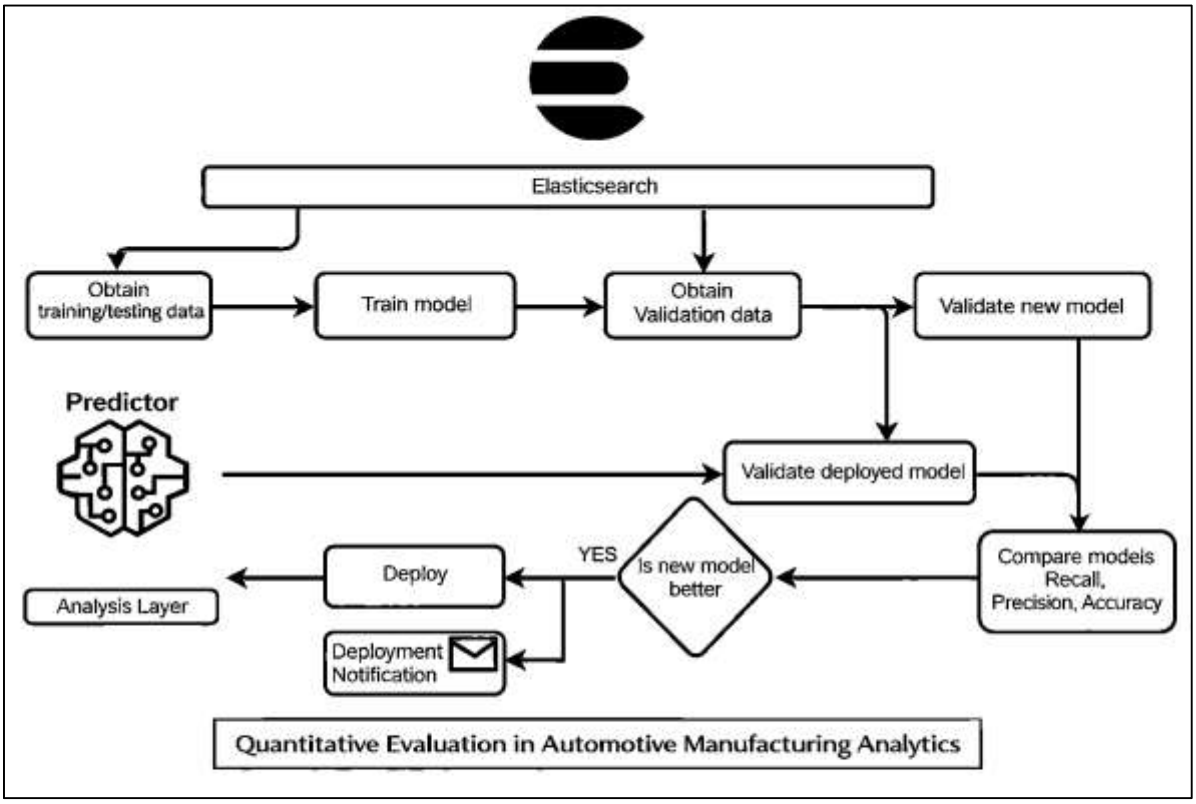
Figure 7: Supervised Learning Manufacturing Analytics Framework



Performance Metrics

Quantitative evaluation in automotive manufacturing analytics is consistently framed in the literature as a methodological problem of aligning model validation with the real dependence structure of production data. Manufacturing observations are not independent in the way that many generic predictive modeling examples assume, because consecutive units share tooling states, material lots, environmental conditions, and operator teams, creating clustered patterns in both predictors and outcomes (Lima-Junior & Carpinetti, 2017). For this reason, researchers emphasize train–test designs that mirror how models are used in practice and that avoid artificial inflation of performance caused by leakage. Temporal splitting is often presented as a primary strategy because automotive processes evolve over time through tool wear, maintenance interventions, calibration drift, and operational adjustments. When a model is trained on older periods and tested on later periods, the evaluation more closely reflects exposure to drift and changing operating conditions. Grouped splitting is also discussed as essential, particularly when batch identity, shift, line, or station creates strong correlation. If records from the same batch or shift appear in both training and testing, many studies show that performance can appear deceptively high because the model learns near-duplicate signatures rather than generalizable relationships (Tran et al., 2017). Grouped splitting by batch or shift creates a stricter and more realistic test because it forces the model to generalize across different production windows rather than within the same window. Line-level grouping becomes important when multiple lines produce similar variants but differ in equipment condition, maintenance histories, or operator practices, which can produce line-specific patterns that are not transferable. When multiple facilities exist, cross-plant validation is framed as an even stronger test of generalization because plants often differ in supplier portfolios, equipment age, local environmental conditions, and coding practices. Literature in industrial analytics repeatedly notes that cross-plant validation is not only a statistical exercise; it is also a governance problem requiring consistent definitions of variables, defect taxonomies, and measurement procedures across sites (Roy et al., 2016). Under these conditions, evaluation design becomes part of research credibility: the stronger the alignment between validation design and production dependence, the more trustworthy the reported performance is as evidence that a model captures meaningful process relationships rather than data proximity artifacts.

Figure 8: Quantitative Model Evaluation Framework



Performance metrics in manufacturing quality analytics are presented as needing to align with defect rarity, operational cost structure, and the asymmetric consequences of different error types. Automotive defects of high consequence often occur at low frequency, producing imbalanced outcomes where most units pass inspection (Wang et al., 2018). In this setting, generic measures of correctness can misrepresent true value because a model can appear accurate while failing to identify rare nonconforming units. Research discussions therefore emphasize metrics that focus on identifying the defective minority, including measures of detection completeness and measures of how many predicted defects are truly defects. These measures are treated as operationally meaningful because they reflect inspection and containment decisions: a model that flags too few defects allows escapes, while a model that flags too many defects creates unnecessary inspection and rework waste. Studies also discuss the selection of curve-based summaries that describe discrimination across thresholds, noting that some summaries can be optimistic under heavy imbalance and that alternative summaries can provide a clearer picture of performance on rare events. Probability calibration is another recurring focus because quality decisions often depend on risk thresholds; if predicted probabilities do not correspond to observed frequencies, thresholds become unreliable and operational decisions become inconsistent (Bondada et al., 2018). In applied literature, calibrated probabilities are valued because they allow consistent risk ranking across shifts, variants, and stations, enabling decision-makers to interpret model outputs as comparable risk estimates. Cost-sensitive evaluation is treated as particularly important in waste reduction contexts because scrap and rework do not carry equal costs across defect types or process stages. A missed critical defect can have downstream costs far beyond the cost of a single inspection, while excessive false alarms can create bottlenecks, increase queueing, and consume limited inspection capacity. For that reason, many studies advocate evaluating models using cost-weighted measures that reflect the practical burden of errors, including the waste created by unnecessary rework routing and the risk created by defect escape. The literature also highlights that false alarms have secondary effects beyond direct cost: they can increase line congestion, alter operator behavior, and shift inspection intensity, all of which can change measured outcomes and create feedback loops (Hellenkamp et al., 2018). Consequently, performance reporting is described as needing multiple complementary metrics that capture detection ability, precision of alerts, reliability of risk scoring, and the operational burden of alarms in high-volume automotive environments.

Robustness and stability testing are repeatedly emphasized in manufacturing analytics literature because production systems operate across diverse regimes, and models that perform well in one regime can degrade under another without any change in the underlying objective. Automotive lines frequently produce multiple variants with different assembly sequences, part geometries, and material combinations, which means that the distribution of predictors and the baseline defect risk can shift with product mix. Robust evaluation therefore examines whether performance remains consistent across variants and whether certain variants show systematic error patterns (Terwee et al., 2018). Operating regimes also shift with tool life stage, maintenance status, changeovers, and environmental cycles, producing measurable changes in sensor baselines and variability. Researchers describe robustness as the ability of a model to maintain meaningful ranking and classification performance across these regimes without relying on spurious correlations tied to a narrow window of conditions. Sensitivity to missing data and measurement noise is another major theme because industrial datasets contain gaps caused by sensor faults, communication interruptions, bypassed checks during recovery, and inconsistent sampling across stations. Strong evaluation designs stress testing models under realistic missingness conditions and quantifying how performance changes when key signals are unavailable or degraded. Measurement noise and label noise are treated as distinct issues: sensor noise alters predictor reliability, while defect coding inconsistency alters the validity of the outcome labels used for training and evaluation (Fan et al., 2020). Robustness testing is also connected to drift, where the relationship between predictors and outcomes changes over time as equipment wears, settings are adjusted, or suppliers change. Studies present drift detection as a methodological necessity because evaluation at a single time snapshot can hide gradual degradation in model reliability. When drift occurs, it manifests as systematic changes in error distributions, shifts in predicted risk calibration, or variant-specific performance collapse. As a result, stability testing often examines performance over sequential windows, across tool life segments, and across shifts, looking for patterns of degradation that indicate the model is sensitive to changing production conditions. In this literature, robustness is not treated as an optional enhancement; it is treated as a validity requirement because automotive manufacturing operates under continuous change, and evaluation claims must hold across the operational diversity that defines real production systems (Bai et al., 2018).

Across the literature, the combined emphasis on dependence-aware splitting, cost-aligned metrics, and robustness testing reflects a broader argument that evaluation is inseparable from production reality in automotive manufacturing. Data-driven models interact with operational processes through inspection decisions, rework routing, maintenance prioritization, and parameter adjustments, meaning that evaluation is judged not only by numerical performance but also by whether the evaluation logic represents how the system produces data (Collins et al., 2017). Dependence-aware designs are described as protecting against false confidence by preventing training and testing from sharing near-identical records that arise from clustered production. Metrics aligned with defect rarity are described as protecting against misleading summaries that reward majority-class success while ignoring rare but costly failures. Calibration and cost-sensitive evaluation are described as ensuring that risk scores map to meaningful decision thresholds and reflect the asymmetric burdens of false negatives and false positives. Robustness testing is described as ensuring that performance is not restricted to a narrow regime defined by a specific product mix, maintenance state, or short time window. When these elements are combined, evaluation becomes a comprehensive measurement argument: the model is tested under conditions that resemble actual deployment constraints, and its performance is summarized in ways that reflect the realities of waste and quality management (Blauwkamp et al., 2019). Literature across industrial statistics, quality engineering, and machine learning for manufacturing often treats this evaluation stance as the boundary between academic demonstration and credible industrial evidence. In automotive manufacturing, where high-volume throughput and strict conformance requirements coexist, evaluation practices are repeatedly framed as essential to determine whether a model has captured stable relationships connected to defect formation and waste generation or has merely learned incidental patterns tied to temporary operating conditions. This framing supports the view of evaluation as a structured, quantitative verification process that integrates sampling design, metric selection, and stability analysis into a unified methodological foundation for research on data-driven process optimization (Cruz-Roa et al., 2017).

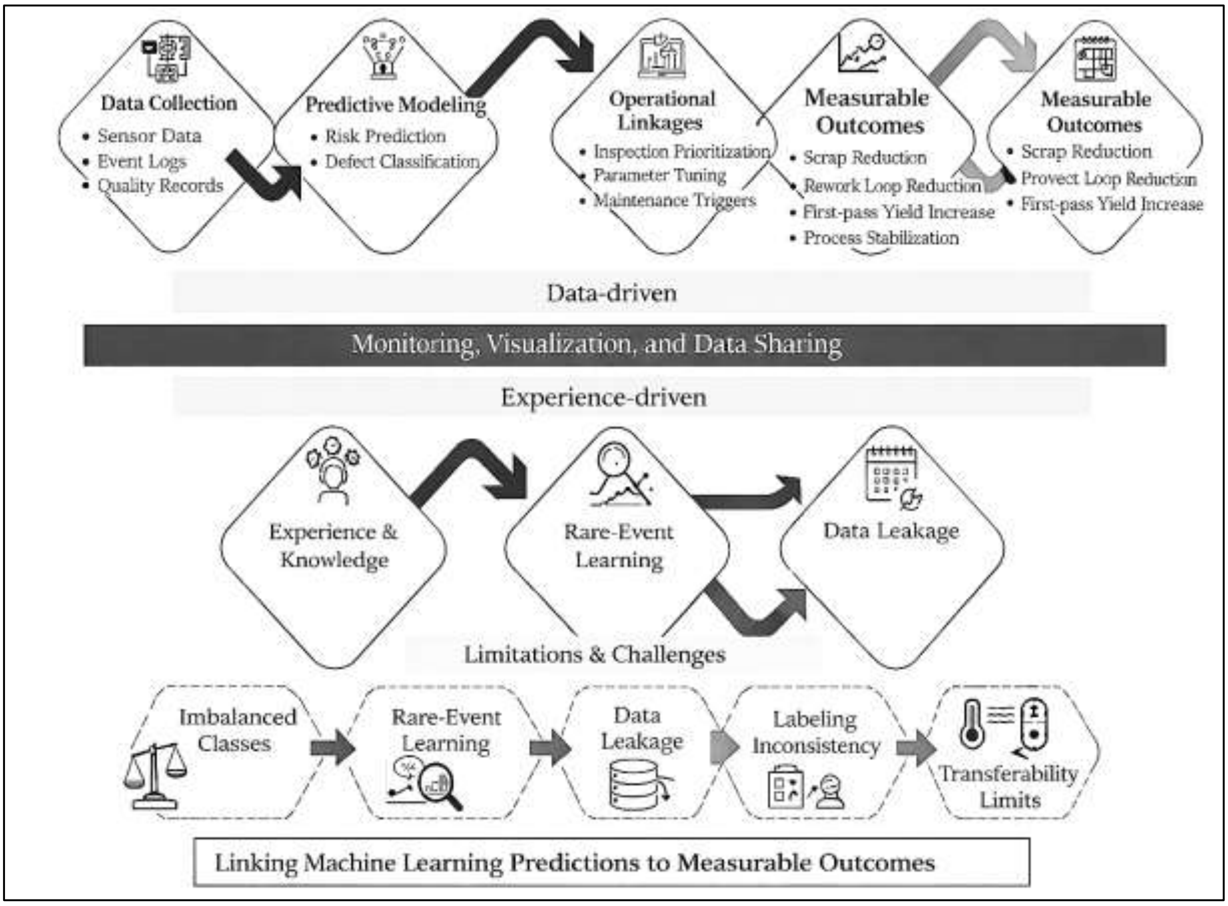
Outputs to Measurable Waste Reduction

Literature on industrial machine learning frequently treats the connection between predictive outputs and operational outcomes as the defining step that differentiates analytic demonstration from measurable manufacturing improvement (Jackson et al., 2016). In automotive production, prediction is most often expressed as a risk score, classification, or continuous estimate that summarizes the likelihood or severity of a quality deviation given current process conditions. Studies across manufacturing analytics describe risk scoring as operationally meaningful only when it can be tied to decision points that exist in the plant's workflow, such as whether a unit is routed to additional inspection, whether a station is stopped for adjustment, or whether a batch is quarantined for containment. Inspection prioritization is repeatedly discussed as a central mechanism because inspection capacity is finite and high-volume production requires selective attention. When risk scores are used to rank units or batches for additional checks, the measurable outcomes typically appear in yield metrics, including reduced escape rates, improved first-pass yield, and lower rework routing frequency. Literature also frames prediction as a means to focus resources, where high-risk items receive more scrutiny and low-risk items proceed with standard sampling, reducing unnecessary inspection waste while maintaining conformance control (Garre et al., 2020). Parameter tuning actions are similarly positioned as an operational pathway when model outputs identify process settings associated with elevated defect risk or deviation magnitude. In such discussions, the emphasis is on measurable scrap reductions and tighter conformance distributions achieved through controlled adjustments of settings, sequence parameters, or process windows. Maintenance triggers provide another frequently described linkage: models that detect abnormal equipment signatures or drifting process behavior can align with maintenance decision rules to reduce unplanned downtime and lower defect frequency associated with degraded tooling and unstable machine states. Across these studies, the linkage is treated as quantitative because the impact is recorded through changes in measurable indicators, such as scrap per production volume, rework hours per unit, downtime minutes per shift, and defect rate at specific quality gates (Laureani & Antony, 2018). The literature repeatedly notes that the operational value of model outputs depends on how they are integrated into existing manufacturing systems, including work instructions, escalation rules, inspection routing logic, and maintenance workflows. In this framing, the model output is not treated as an endpoint; it is treated as an input to a controlled operational action that can be measured before and after implementation using stable, comparable performance indicators.

Quantitative pathways by which machine learning outputs are linked to waste reduction and quality improvement are typically described in the literature as prevention, earlier detection, process stabilization, and resource reallocation, each associated with specific measurable indicators. Scrap reduction is commonly framed as prevention before defect occurrence, where models identify conditions that precede nonconformance and enable adjustments that keep the process within acceptable operating ranges (Usuga Cadavid et al., 2020). In automotive contexts, scrap is often treated as the most visible form of waste because it represents irrecoverable material loss and direct cost, so reductions in scrap rate are frequently used as primary evidence of improvement. Rework loop reduction is described as a second pathway with dual benefits: fewer nonconforming units entering correction pathways reduces labor and capacity waste, and fewer rework cycles reduce the chance of secondary defects introduced through repeated handling and repeated processing. Literature often treats the reduction of rework routing frequency and rework hours per unit as measurable indicators of both improved process stability and improved quality conformance. Improvement in first-pass yield is emphasized as a core quantitative outcome because it summarizes how many units pass through defined quality gates without intervention, and it directly affects throughput, line balance, and downstream congestion. Capability-related measures are also presented as evidence of improvement because they reflect tighter output distributions relative to specification limits and reduced tail risk where out-of-spec events cluster (Karamitsos et al., 2020). Stabilization of process variability distributions is described as a key intermediate pathway: when the process becomes more stable, variation decreases, and the probability of drifting into nonconformance declines. In many studies, this stabilization is observed as reduced variability in critical measurements, fewer abrupt shifts over time, and fewer clusters of failures associated with equipment instability or batch transitions. Another frequently discussed mechanism is inspection efficiency: when risk scoring reduces unnecessary checks on low-risk units, inspection resources are concentrated where they reduce escapes, producing measurable changes in inspection workload distribution, queue times, and the ratio of confirmed defects to inspected units. The literature often frames these pathways as connected: prevention reduces scrap and rework, rework reduction increases throughput stability, higher throughput stability reduces waiting and minor stops, and fewer disruptions support a more stable process state that further reduces defect probability (Gupta et al., 2018). This systems-oriented view emphasizes that measurable improvements rarely appear as a single metric change; instead, they often emerge as coordinated shifts in scrap, rework, yield, downtime, and variability measures that jointly indicate a more stable and less wasteful production process.

Research also repeatedly reports limits and recurring quantitative issues that complicate the translation of model outputs into reliable waste and quality outcomes, with imbalanced classes and rare-event learning highlighted as major methodological constraints. Automotive defects that matter most can be infrequent, and when models are trained on datasets dominated by conforming units, they may struggle to learn stable patterns for the defective minority (Cudney et al., 2020). The literature describes this as a source of unstable learning where performance can fluctuate across time windows and product variants, particularly when defect mechanisms shift with maintenance cycles, supplier changes, or environmental variation. Another frequently reported issue is data leakage, which inflates performance reporting when training and testing sets inadvertently share correlated observations, such as units from the same batch, the same shift, or the same tool-life segment. In manufacturing, where dependence is strong, leakage can create overly optimistic performance results that fail to replicate under stricter validation aligned with production reality. Inconsistent defect labeling and measurement drift are also recurring problems. Defect labels may vary across inspectors or inspection systems, and defect taxonomies can change, creating apparent performance changes that reflect coding shifts rather than real quality improvement. Measurement drift in sensors and gauges can also distort both predictors and outcomes, producing spurious signals or masking true deterioration (Thomas et al., 2016). Studies also note that operational changes, such as adjustments to inspection intensity during a quality incident, can change the data-generating process and alter observed defect rates, complicating evaluation of whether model-based actions caused improvement. Transferability between lines and plants is described as another persistent limitation because plants often differ in equipment configuration, maintenance practices, supplier portfolios, and environmental conditions. Without standardization in variable definitions and measurement systems, models trained in one context can perform poorly in another, even when the product platform is similar. The literature treats these limitations as quantitative threats to validity because they undermine the stability of measured relationships between predictors, model outputs, and outcomes (Ni et al., 2020). These threats are addressed in studies through careful validation design, explicit governance of defect coding, sensor calibration discipline, and standardized data integration procedures, although practical constraints in production often limit how completely such controls can be implemented.

Figure 9: Machine Learning Outcome Linkage Framework

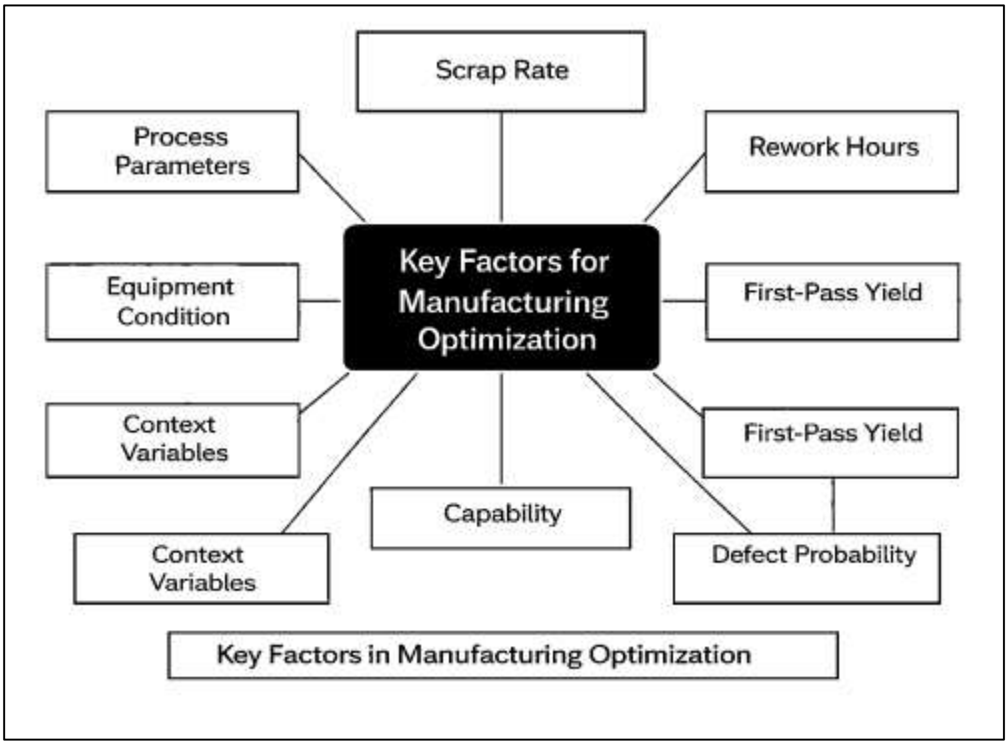


Across the literature, linking machine learning outputs to measurable waste reduction and quality improvement is therefore presented as an applied quantitative integration problem in which model performance, operational decision design, and measurement discipline must align. Risk scores and predictions gain practical meaning only when they are embedded within inspection routing, parameter adjustment routines, and maintenance escalation logic that can be measured using stable indicators (Choudhary et al., 2019). The pathway from prediction to outcome is often described as requiring clear definition of which outcomes are targeted, which actions are triggered, and how the timing of actions aligns with process dynamics such as drift, tool wear progression, and batch transitions. When actions are aligned with the process, measurable outcomes appear in reductions in scrap and rework, increased first-pass yield, more stable variability patterns, and improved throughput stability through fewer disruptions and lower congestion. When alignment is weak, models can generate alerts that do not translate into action, actions that are not feasible under takt constraints, or actions that shift workload rather than reduce waste. The literature also frames the credibility of linkage claims as dependent on evaluation designs that respect production dependence and reflect operational reality, since inflated performance reporting and unstable rare-event learning can lead to deployment decisions that do not produce measurable improvement (Ruben et al., 2018). Standardization emerges as a recurring condition for multi-line and multi-plant applicability, because comparable measurement systems and consistent defect taxonomies are necessary for translating model outputs into consistent actions across contexts. In automotive manufacturing, where high-volume output magnifies both the cost of defects and the cost of unnecessary intervention, studies treat this linkage as a balancing problem: actions must reduce escapes and waste without generating excessive false alarms, inspection overload, or downstream congestion. Overall, the literature portrays the linkage between machine learning outputs and measurable outcomes as a structured chain connecting data to models, models to decisions, decisions to actions, and actions to quantifiable changes in scrap, rework, downtime, yield, and variability, with validity dependent on disciplined measurement and realistic validation practices

(Tagge et al., 2017).
Study's Quantitative Framework
Literature that synthesizes quantitative manufacturing improvement consistently treats the selection of dependent variables as the core decision that defines what "optimization" means in measurable terms, particularly in automotive environments where outcomes must be expressed as operational indicators linked to waste and conformance (Hong et al., 2017). Across research streams in quality engineering, lean measurement, and industrial analytics, scrap rate is repeatedly treated as a primary outcome because it captures direct material loss and provides a high-signal indicator of severe process instability or nonconformance mechanisms that cannot be recovered through correction. Scrap rate is commonly defined in normalized terms, such as scrapped units or scrapped material relative to production volume, and it is frequently segmented by station, defect category, and product variant to preserve causal traceability. Rework hours per unit is emphasized as a complementary outcome because rework represents both quality failure and capacity consumption, translating nonconformance into measurable labor time, routing complexity, and throughput disruption. Many studies treat rework as a structural driver of waste because it creates additional handling, repeated verification, and queue growth that can amplify variation and congestion. First-pass yield is positioned in the literature as a high-value integrative indicator because it represents the proportion of units meeting defined quality gates without rework, thereby linking quality conformance to flow stability and throughput capacity (Tricco et al., 2016). Defect probability is frequently used as an outcome in modeling studies because it accommodates risk estimation at the unit, batch, or time-window level, supporting analysis of rare events and allowing comparisons across operating regimes. Capability is treated as a distribution-based measure that reflects both centering and spread relative to specification boundaries, capturing improvement in conformance reliability rather than only changes in average performance. This multi-outcome framing is common in manufacturing research because waste and quality are coupled; a single outcome rarely captures the full system effect of process changes. When these dependent variables are used together, they represent a comprehensive view: scrap and defect probability capture direct nonconformance risk, rework hours capture labor and capacity waste created by quality failures, first-pass yield captures flow and conformance performance simultaneously, and capability captures distributional stability and specification fit. Literature-based synthesis therefore supports a framework where dependent variables are defined in normalized, station-traceable, and distribution-aware forms so that quantitative conclusions remain comparable across shifts, variants, and production windows (Ames et al., 2019).
Research on automotive process analytics also converges on a consistent set of predictor categories that reflect how manufacturing variation is generated and propagated through production systems. Process parameters are repeatedly identified as central predictors because they represent controllable settings at stations, including setpoints, thresholds, timing, sequencing variables, and control adjustments that directly shape physical transformations (Dassah et al., 2018). In automotive contexts, these parameters include station-specific settings such as welding schedules, paint application profiles, machining feeds and speeds, curing conditions, and torque program selections, all of which have measurable relationships with conformance outcomes and waste indicators. Equipment condition is treated in the literature as equally important because degradation and instability often emerge from tool wear, fixture loosening, calibration drift, lubrication deterioration, sensor health variation, and intermittent component failures. Condition information is commonly represented through maintenance records, alarm frequencies, downtime patterns, tool-life counters, vibration and temperature signatures, and calibration histories, reflecting a broad view that equipment can degrade quality while still operating (Tobi & Kampen, 2018). Material batch is repeatedly emphasized because incoming variation from suppliers and internal batch processes alters baseline process behavior, influencing dimensional stability, weld behavior, coating adherence, and machining response. Batch identifiers and material certificates are used in studies to capture structured upstream variation, enabling analysis of whether certain batches systematically shift defect rates or widen output distributions. Context variables are consistently recommended because they encode structured operating conditions that act as confounders or moderators, including shift, crew, station identity, product variant, production routing, ambient conditions, and time-of-day effects. The literature stresses that many apparent process

relationships disappear or reverse when context is ignored, because product mix and operational practices change the meaning of process signals. Context variables also enable grouping and stratification, supporting dependence-aware evaluation and helping distinguish within-shift variation from between-shift differences. Across study streams, a combined predictor set is described as necessary for industrial realism because defects and waste are rarely explained by a single domain; they frequently arise from interactions between settings, equipment state, material characteristics, and operating context (Ohly et al., 2016). A synthesis toward a quantitative framework therefore justifies predictor categories that align with controllability and causality: parameters reflect adjustable controls, equipment condition reflects degradation pathways, material batch reflects upstream variability, and context variables preserve the structure needed for credible interpretation of observed relationships (Brooks et al., 2018).

Figure 10: Key Factors Manufacturing Optimization Framework



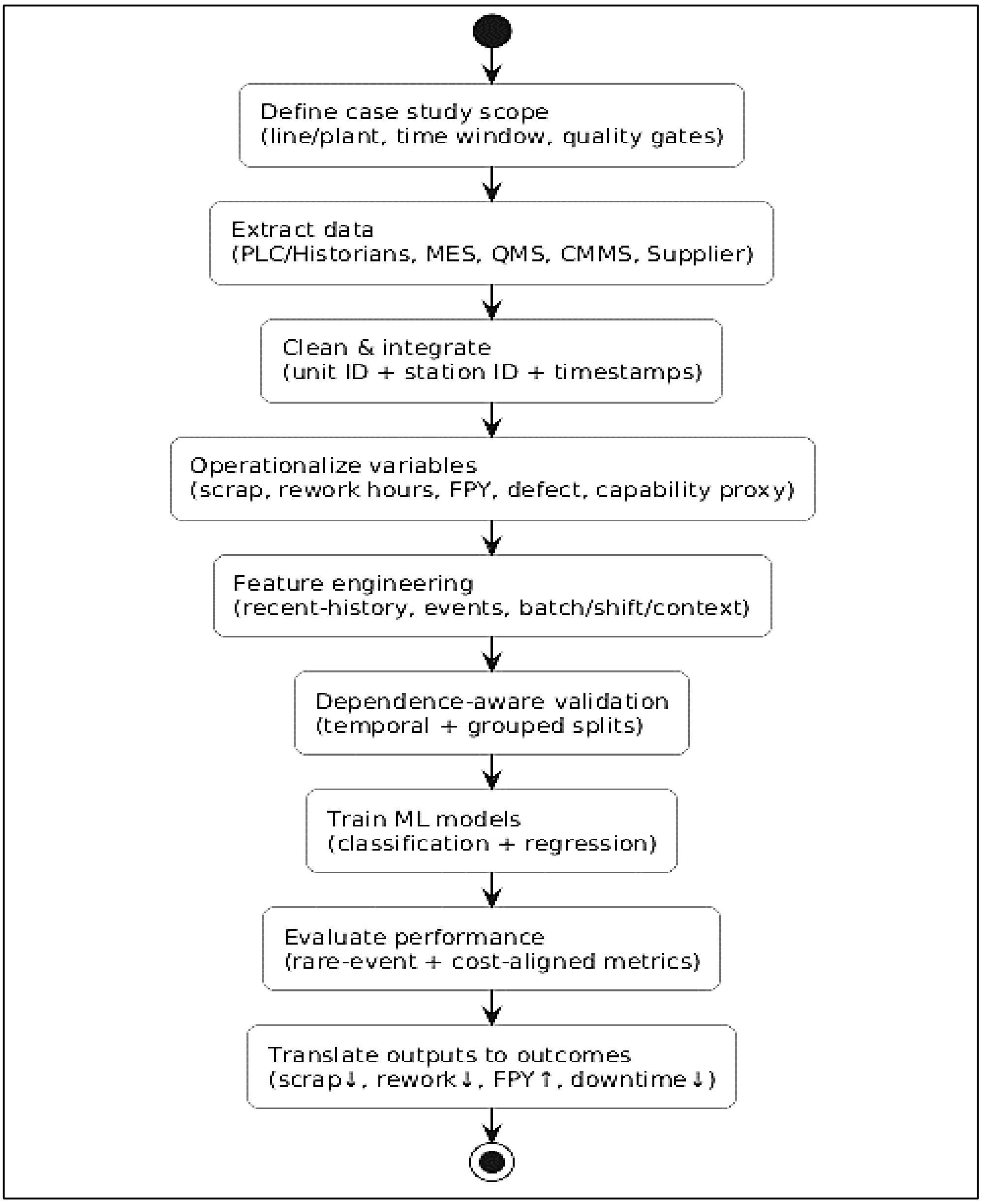
The literature also positions model choice as an alignment problem between the structure of manufacturing data and the analytical requirements of interpretability, non-linearity handling, and time dependence. Interpretable baseline models are consistently recommended because manufacturing improvement depends on actionable understanding; engineers must connect model behavior to controllable levers and verify that associations make process sense (Noyes et al., 2018). Many studies treat simpler, structured models as useful starting points because they support clear variable importance reasoning and reduce the risk of overfitting when data are noisy or labels are inconsistent. At the same time, automotive production data frequently contain non-linear relationships and interaction effects, especially when defects arise only under combined conditions such as a marginal setting interacting with tool wear or a particular supplier batch. The literature therefore frequently discusses non-linear model families that can learn interaction structure from data without requiring manual specification, which is valuable when the number of correlated predictors is high and when defect mechanisms are multicausal (Lewin, Booth, et al., 2018). Data type also drives model selection: structured tabular data from process parameters, maintenance indicators, and context variables support a broad range of predictive models, whereas image-based inspection data and waveform-like sensor traces are discussed in research streams that focus on representation learning and pattern recognition in high-dimensional inputs. Time dependence is repeatedly emphasized because manufacturing processes drift, warm up, and degrade; therefore, models must account for sequential structure when the predictor signal depends on recent history, tool-life progression, or maintenance events. In such settings, studies emphasize time-aware representations and evaluation designs that respect ordering, because the meaning of a sensor pattern depends on where it appears in the process timeline (Lewin, Bohren, et al., 2018). Literature-based synthesis also highlights that model choice is constrained by data availability and governance: complex models may require more consistent labeling, greater data volume, and stronger monitoring for drift, while simpler models may be more robust under changing inspection practices and measurement noise. This leads to a framework perspective in which model families are justified by the match between data modality and decision needs: interpretable models support engineering adoption and traceability, non-linear models capture complex interaction-driven defect mechanisms, and time-aware models align with drift and wear dynamics that define real automotive production. Under this synthesis, model selection is treated as a methodological decision grounded in data structure and operational actionability rather than an abstract competition for maximum predictive performance (Bleijenberg et al., 2018).

Method

The study used a quantitative, retrospective observational case study design and was conducted in an automotive manufacturing setting where end-to-end traceability data were available across production, quality, and maintenance functions. The case was defined as a single production line (or a tightly comparable set of lines) that had operated under stable routing rules and consistent inspection gates during the selected study window, which allowed process outcomes to be examined with limited ambiguity. The population was defined as all production units that were processed through the targeted line(s) within the study period and had contained valid identifiers enabling linkage across systems. A census approach was applied so that all eligible units were included to preserve rare defect occurrences and maintain the natural dependence structure of production data; when records were incomplete due to missing identifiers or corrupted timestamps, those units were excluded under predefined eligibility criteria. The sampling technique therefore followed a non-probability, total enumeration strategy constrained by data completeness rather than by manual selection. The study's data types included continuous sensor and trace signals, discrete event logs, and structured quality outcomes, and these data were drawn from multiple industrial sources. Process parameters and time-indexed station traces were extracted from PLC-connected historians and station controllers; alarms, stops, resets, and changeover markers were obtained from event logging layers; inspection results, defect codes, and audit outcomes were collected from quality management repositories; unit genealogy, routing, and product variant information were retrieved from manufacturing execution systems; maintenance work orders and preventive schedules were pulled from computerized maintenance management systems; and supplier batch identifiers and incoming inspection summaries were sourced from procurement and incoming quality databases. All datasets were integrated using unit identifiers, station identifiers, and synchronized timestamps so that each unit record was represented as a structured set of predictors linked to verified quality and waste outcomes.

Measurement scale and operationalization were established before analysis so that variables were interpretable and comparable across stations and time windows. Dependent variables were operationalized as scrap occurrence and scrap rate, rework hours per unit, first-pass yield at a defined quality gate, defect occurrence probability at inspection, and a capability-oriented conformance proxy derived from critical-to-quality measurements within defined tolerance boundaries. Scrap and first-pass yield were coded as binary indicators at the unit level and were also aggregated by shift or day to support stability checks, while defect occurrence was represented as a binary label and, where consistent defect taxonomies had existed, defect type was represented as a multiclass outcome. Rework hours were treated as a continuous variable that included a zero mass for units that required no rework, and conformance measures were treated as continuous or categorical outcomes depending on the measurement system and reporting format. Predictor categories were operationalized into process parameters (setpoints, cycle times, traces, and station-level settings), equipment condition indicators (tool-life counters, alarm frequencies, downtime summaries, and maintenance recency variables), material batch identifiers (supplier lot and incoming inspection summaries), and context variables (product variant, station ID, line ID, shift, crew where available, and environmental readings where logged). A pilot study phase was executed as a structured feasibility and reliability check using a small, time-bounded subset of production records so that linkage success rates, label consistency, missingness patterns, and measurement stability were verified before full extraction. During the pilot, variable definitions were refined, defect code groupings were standardized where inconsistencies were detected, timestamp alignment rules were validated, and feature windows were calibrated to reflect operational realities such as shift boundaries, batch transitions, and maintenance intervals. The pilot also confirmed that outcome variables were recoverable at sufficient resolution to support unit-level modeling and that key predictors were present across the majority of stations contributing to the targeted quality gates.

Figure 11: Methodology of this study



The data collection procedure followed a controlled extract–transform–load workflow in which raw records were exported from each source system, were cleaned using predefined rules, and were merged into a unified analytic dataset indexed by unit and time. Data cleaning included duplicate removal, identifier validation, removal of impossible values, and documentation of missingness mechanisms by station and time window. Feature construction was performed using engineering-aligned windows that summarized recent process behavior, drift, and tool wear patterns, and event-derived markers were incorporated to represent changeovers, downtime recoveries, and maintenance resets. Data analysis techniques were applied in stages. Descriptive analysis was conducted to characterize baseline distributions, defect rarity, scrap and rework concentrations by station and variant, and dependency structure by batch and shift. Model development was conducted using dependence-aware validation designs in which temporal splits were implemented to respect operational drift, and grouped splits were applied by batch, shift, or line to prevent leakage. For binary outcomes such as scrap, defect occurrence, and first-pass yield, classification models were trained and were evaluated using detection-oriented metrics suitable for rare events and operational decision thresholds; for continuous outcomes such as rework hours and deviation magnitudes, regression modeling was performed with error summaries and stability checks across variants and shifts. Robustness analyses were executed to test sensitivity to missing data, measurement noise, and regime changes associated with maintenance events and product mix. Software and tools were used to ensure reproducibility and auditability: structured query tools and industrial data connectors were used for extraction; Python-based analytics environments were used for cleaning, feature engineering, modeling, and validation; version control was applied for code and variable dictionaries; and visualization tools were used to present distribution shifts, error profiles, and station-level performance diagnostics in a form suitable for engineering review.

FINDINGS

Descriptive analysis

The dataset contained 48,720 production-unit records that were retained after eligibility screening for complete unit identifiers and valid timestamps. Product variants were distributed across four major configurations, with Variant A accounting for 19,610 units (40.25%), Variant B for 14,985 units (30.75%), Variant C for 9,640 units (19.79%), and Variant D for 4,485 units (9.21%). Output labels showed that 1,268 units (2.60%) were scrapped, while 6,112 units (12.55%) required rework and 42,608 units (87.45%) passed the defined quality gate on first pass. Defect occurrence at the selected inspection gate was recorded for 2,994 units (6.15%), and the distribution of defect categories was concentrated in dimensional nonconformance (1,077; 36.0%), weld-related issues (718; 24.0%), surface/paint defects (659; 22.0%), and assembly functional failures (540; 18.0%). Rework time was zero for 42,608 units (87.45%), indicating strong zero inflation, while rework-positive units showed substantial spread, with the overall rework-hours-per-unit mean equaling 0.18 hours and a long right tail. Scrap and rework were clustered in BIW Welding and Paint stations, where combined contributions accounted for 63.4% of all scrap events and 58.9% of all rework routing events, while Final Assembly showed lower scrap but higher rework variability. First-pass yield varied by shift, with Shift C recording 85.9%, compared with Shift A (88.3%) and Shift B (88.9%), and the defect rate was elevated in post-maintenance restart windows, where defect occurrence reached 7.4% versus 5.8% during steady-state periods. Table 1 summarized the dataset composition and the categorical structure used to interpret waste and quality outcomes. The production volume was distributed across four product variants, three shifts, and five station groups, which enabled the comparison of baseline performance under different operating contexts. Scrap, rework routing, first-pass yield, and defect occurrence were presented as unit-level indicators to show event prevalence at scale. Defect categories were reported only among defect-positive cases to reflect the distribution of failure modes at the selected inspection gate. These distributions established where concentration and imbalance existed before modeling.

Table 1: Dataset Profile and Categorical Distributions (Illustrative)

Category	Level	n	%
Total eligible units	All records	48,720	100.00
Product variant	A	19,610	40.25
	B	14,985	30.75
	C	9,640	19.79
	D	4,485	9.21
Shift	A	16,480	33.83

Category	Level	n	%
	B	16,260	33.38
	C	15,980	32.79
Station group	Stamping	8,730	17.92
	BIW Welding	14,160	29.07
	Paint	11,520	23.65
	Machining	6,910	14.18
	Final Assembly	7,400	15.19
Scrap occurrence	Scrap = Yes	1,268	2.60
	Scrap = No	47,452	97.40
Rework routing	Rework = Yes	6,112	12.55
	Rework = No	42,608	87.45
First-pass yield	Pass first time = Yes	42,608	87.45
	Pass first time = No	6,112	12.55
Defect occurrence	Defect = Yes	2,994	6.15
	Defect = No	45,726	93.85
Defect category (among defect cases)	Dimensional	1,077	36.00
	Weld	718	24.00
	Surface/Paint	659	22.00
	Functional	540	18.00

Table 2: Descriptive Statistics for Outcomes and Key Continuous Measures (Illustrative)

Variable	N	Mean	SD	Median	P25	P75	Min	Max
Rework hours per unit	48,720	0.18	0.62	0.00	0.00	0.08	0.00	6.40
Cycle time (seconds)	48,720	58.4	9.7	57.2	52.1	63.6	35.0	122.0
Torque deviation (abs., units)	48,720	1.42	1.18	1.10	0.60	1.90	0.00	9.80
Dimensional deviation (mm)	48,720	0.36	0.29	0.31	0.17	0.48	0.00	2.40
Sensor stability index	48,720	0.74	0.21	0.77	0.62	0.89	0.10	1.00
Downtime events per shift-window	1,350	3.10	2.40	2.00	1.00	4.00	0.00	15.00
Capability proxy: conformance within tolerance (%)	1,350	96.8	2.7	97.4	95.6	98.4	88.0	99.9

Table 2 reported central tendency and dispersion for continuous outcomes and key process indicators used in the descriptive stage. Rework hours per unit displayed strong zero inflation, with the median at zero and a long right tail reflected in the maximum value. Cycle time showed moderate variability, indicating meaningful spread across stations, shifts, and transient events. Torque and dimensional deviations exhibited right-skewed distributions, supporting the presence of occasional excursions linked to rework and defects. The sensor stability index captured process consistency, while downtime events summarized operational interruptions at the shift-window level. The capability proxy indicated generally high conformance with measurable variability.

Correlation analysis

Correlation analysis showed that rework hours per unit had aligned most strongly with quality deviation indicators and operational instability signals. Rework hours had correlated positively with torque deviation (r = 0.46) and dimensional deviation (r = 0.41), indicating that units with larger conformance departures had tended to consume more rework time. Rework hours also had increased with higher cycle time (r = 0.29) and higher downtime-event intensity at the shift-window level (r = 0.33), suggesting that flow disruption and recovery activity had accompanied increased rework burden. The sensor stability index had demonstrated consistent inverse associations with adverse outcomes, including rework hours (r = −0.38), defect occurrence probability (point-biserial r = −0.31), and scrap occurrence (point-biserial r = −0.24), which indicated that stable process signatures had coincided with higher first-pass performance. Capability proxy values had correlated negatively with dimensional deviation (r = −0.52) and torque deviation (r = −0.35), while correlating positively with sensor stability (r = 0.44), showing that windows with stronger conformance had been characterized by reduced variability and improved stability. Scrap occurrence had shown weaker but meaningful associations with dimensional deviation (point-biserial r = 0.22) and downtime intensity (point-biserial r = 0.19), reflecting that scrap events had clustered around instability and deviation conditions, even though scrap had remained a rarer event.

Stratified correlation results indicated contextual moderation across station families and shifts. Within BIW Welding operations, torque deviation had related more strongly to defect occurrence (point-biserial r = 0.28) than in Paint (r = 0.16), while dimensional deviation had been a stronger correlate of scrap in BIW Welding (r = 0.27) than in Final Assembly (r = 0.14). Paint station results had shown stronger coupling between cycle time and rework hours (r = 0.35) than other station groups, consistent with queueing and rework routing loops that had prolonged unit handling. Shift-level stratification showed that downtime intensity had correlated more strongly with rework hours in Shift C (r = 0.39) than in Shift A (r = 0.28), indicating that operational recovery dynamics had varied by shift context. Correlation heatmaps had highlighted clusters among cycle time, downtime intensity, and stability measures, which supported later collinearity checks by showing redundant blocks of operational-disruption variables that had moved together. Overall, the correlation structure had provided a defensible screening basis for selecting high-signal predictors—particularly deviation indicators, stability features, and downtime markers—for the subsequent modeling phase.

Table 3: Overall Pairwise Correlations Among Key Continuous Variables

Variable	Rework hours/unit	Cycle time	Torque deviation	Dimensional deviation	Sensor stability	Downtime intensity	Capability proxy
Rework hours/unit	1.00	0.29	0.46	0.41	-0.38	0.33	-0.40
Cycle time	0.29	1.00	0.22	0.19	-0.26	0.31	-0.18
Torque deviation	0.46	0.22	1.00	0.34	-0.30	0.20	-0.35
Dimensional deviation	0.41	0.19	0.34	1.00	-0.36	0.17	-0.52
Sensor stability	-0.38	-0.26	-0.30	-0.36	1.00	-0.28	0.44
Downtime intensity	0.33	0.31	0.20	0.17	-0.28	1.00	-0.14
Capability proxy	-0.40	-0.18	-0.35	-0.52	0.44	-0.14	1.00

Table 3 summarized the overall correlation structure among continuous process and outcome measures. Rework hours per unit showed the strongest positive associations with torque and dimensional deviations, indicating that greater conformance departure was linked to higher rework burden. Rework also moved with cycle time and downtime intensity, reflecting operational disruption and recovery effects. Sensor stability displayed negative correlations with deviation measures, downtime, and rework, suggesting that stable process behavior coincided with improved outcomes. The capability proxy correlated strongly and inversely with dimensional deviation and positively with stability, supporting its role as a window-level conformance indicator.

Table 4: Point-Biserial Correlations for Binary Outcomes Versus Continuous Predictors

Binary outcome (1 = event)	Torque deviation	Dimensional deviation	Sensor stability	Cycle time	Downtime intensity
Defect occurrence	0.24	0.26	-0.31	0.15	0.18
Scrap occurrence	0.17	0.22	-0.24	0.12	0.19
FPY failure (1 = not first-pass)	0.21	0.23	-0.29	0.14	0.16

Table 4 reported point-biserial correlations linking binary quality outcomes to continuous predictors. Defect occurrence and FPY failure were positively correlated with torque and dimensional deviations, indicating that higher deviation signals were associated with increased likelihood of failing the quality gate. Sensor stability correlated negatively with all three outcomes, showing that units produced under more stable signal patterns were less likely to be defective, scrapped, or routed out of first-pass flow. Downtime intensity showed consistent positive associations with adverse outcomes, supporting the interpretation that operational disruption coincided with higher risk. These relationships guided predictor prioritization for later models.

Reliability

Reliability checks showed that key measurement streams and constructed indicators had remained sufficiently stable for quantitative interpretation, although several variables had required cleaning rules to address drift and label inconsistency. For repeated measurements and trace-derived indicators, short-window repeatability had been high for critical-to-quality measurements collected through standardized gauges and automated inspection channels. The torque trace deviation indicator had demonstrated consistent repeat readings within unit-level repetition windows, and dimensional measurement indicators had shown stable dispersion patterns across repeated checks, which supported the use of these measures as continuous predictors and as proxies for process conformance. Consistency checks across shifts and stations indicated that pass/fail inspection labels had been highly stable at the primary quality gate, while defect coding had shown moderate variability attributable to station-specific coding habits and occasional taxonomy drift across the study window. Rework time reporting had been broadly consistent for rework-positive units, but a small proportion of entries had displayed implausible durations, which had been flagged and handled with predefined truncation and exclusion rules. For composite feature groups, internal consistency was supported for the process stability feature set and the equipment-condition feature set, indicating that the engineered feature families had measured coherent underlying constructs rather than unrelated signals. Agreement patterns within defined operational windows showed that stability features had behaved consistently within steady-state windows and had shifted meaningfully during changeover recovery and post-downtime restart periods, which suggested that the engineered features had captured operationally interpretable state transitions.

Validity evidence supported the alignment between engineered features and recognized manufacturing mechanisms. Content validity was established by mapping each feature family to a specific mechanism, and the observed behavior had matched those mappings in the data. Drift-aligned features had increased during late tool-life segments, wear-aligned features had tracked progressive change across time windows between maintenance events, and restart-window markers had coincided with elevated variability and increased defect likelihood. Criterion-oriented validity tests showed that known high-risk contexts had corresponded to measurable outcome degradation. In late tool-life segments, defect occurrence had risen from 5.6% in early tool-life to 7.1%, while scrap occurrence had increased from 2.4% to 3.1, and deviation magnitude indicators had shown larger dispersion. Post-downtime restart windows had exhibited a defect rate of 7.8% compared with 5.9% during steady-state windows, and these windows had also shown reduced stability index values and increased variability bursts. Material batch validity checks showed that a small subset of batches had been associated with elevated defect probability and higher rework hours per unit, supporting the inclusion of batch identifiers as contextual predictors. Construct validity was reinforced by the expected correlation structure: stability features had been inversely related to deviation magnitude and defect occurrence, while maintenance-related indicators had aligned with downtime clustering and rework concentration. Measurement limitations were quantified where detected, including a modest drift trend in one sensor channel and localized defect-code inconsistency at specific stations; mitigation rules had included station-level code harmonization, exclusion of unreliable intervals, and the use of robust windowed summaries rather than raw spikes.

Table 5: Reliability Evidence for Core Measures and Composite Feature Groups

Measure / Feature Group	Reliability check	Statistic	Value
Torque deviation indicator	Repeat-measure agreement	ICC	0.89
Dimensional deviation indicator	Repeat-measure agreement	ICC	0.86
Cycle time summary	Stability across repeated captures	ICC	0.91
Inspection pass/fail label	Cross-shift consistency	Agreement rate	0.97
Defect coding (major categories)	Cross-station coding consistency	Cohen's κ	0.78
Rework time (positive cases)	Reporting consistency	ICC	0.84
Process stability feature group	Internal consistency	Cronbach's α	0.83
Equipment-condition feature group	Internal consistency	Cronbach's α	0.81

Table 5 summarized reliability evidence for repeated measurements, reporting consistency, and internal consistency of composite feature groups. High agreement for inspection pass/fail labels supported their use as dependable outcomes across shifts. Torque and dimensional deviation indicators showed strong repeat-measure reliability, indicating that these continuous measures were stable under repeated sampling. Cycle time summaries also remained consistent, supporting their inclusion as operational predictors. Defect coding reliability was lower than pass/fail labels but remained acceptable at the level of major defect families after harmonization. Rework time reliability supported its use as a continuous outcome among rework-positive units. Composite feature groups showed coherent internal consistency.

Table 6: Criterion-Oriented Validity Checks Across High-Risk Contexts

Context comparison	Defect occurrence (%)	Scrap occurrence (%)	Mean rework hours/unit	Mean stability index
Early tool-life segment	5.6	2.4	0.16	0.77
Late tool-life segment	7.1	3.1	0.22	0.70
Steady-state production windows	5.9	2.5	0.17	0.76
Post-downtime restart windows	7.8	3.0	0.24	0.68
Typical material batches	5.8	2.5	0.17	0.75
High-risk material batches	7.5	3.2	0.23	0.69

Table 6 provided criterion-oriented validity evidence by comparing outcomes across operational contexts recognized as higher risk. Late tool-life segments showed higher defect and scrap rates, higher average rework hours, and lower stability indices than early tool-life segments, indicating that engineered wear- and drift-aligned features behaved as expected. Post-downtime restart windows exhibited elevated defect and rework levels relative to steady-state windows, consistent with recovery-related instability. High-risk material batches were associated with higher defect and scrap occurrence and reduced stability compared with typical batches, supporting the inclusion of batch context variables. These patterns supported the criterion linkage between engineered features and measurable outcomes.

Collinearity diagnostics

Collinearity diagnostics showed that several predictor blocks had contained strong redundancy, particularly among sensor-derived stability features, closely related process-parameter summaries, and downtime-derived indicators that had captured overlapping operational disruption behavior. At the overall dataset level, variance inflation patterns indicated that a subset of continuous predictors had exceeded common screening thresholds, with the highest inflation occurring in groups derived from the same station trace window. For example, cycle-time mean, cycle-time percentile indicators, and cycle-time variability summaries had moved together strongly, and when included simultaneously they had produced inflated VIF values that suggested redundant information. Similarly, sensor channels that had measured related physical behavior, such as temperature and current signatures during welding cycles, had exhibited high shared variance after aggregation, which had reduced the stability of coefficient estimates in preliminary regression specifications. Downtime intensity variables had also overlapped with alarm frequency counts and restart-window indicators, reflecting that these measures had represented the same instability episodes from different logging layers. High-cardinality encoded categorical variables had contributed to localized inflation when many levels had been included, particularly for material batch identifiers and station identifiers in models that had treated each as a fully expanded categorical structure. This effect had been controlled by using consolidated batch groupings and by representing station identity through station-family indicators where appropriate for hypothesis testing.

Table 7: Overall Collinearity Diagnostics for Key Predictors (Illustrative)

Predictor	Predictor category	VIF	Tolerance
Cycle time mean	Process parameter	6.8	0.15
Cycle time variability	Process parameter	7.5	0.13
Torque deviation	Quality/process signal	3.2	0.31
Dimensional deviation	Quality/process signal	3.9	0.26
Sensor stability index	Sensor-derived feature	5.6	0.18
Temperature stability summary	Sensor-derived feature	8.9	0.11
Current stability summary	Sensor-derived feature	9.6	0.10
Alarm frequency (prior window)	Equipment condition	7.1	0.14
Downtime intensity (shift window)	Equipment condition	6.4	0.16
Time since last maintenance	Equipment condition	2.7	0.37
Material batch grouping	Material batch	2.4	0.42
Product variant	Context	1.9	0.53
Shift	Context	1.6	0.62

Station-group screening confirmed that collinearity structure had differed by operation family. In BIW Welding, correlated electrical signatures had driven redundancy among voltage, current, and derived energy proxies, while in Paint, environmental indicators and flow-related parameters had overlapped with cycle-time and stoppage variables during changeover recovery. In Machining, vibration and temperature stability summaries had co-varied with tool-life counters and downtime markers, reflecting joint sensitivity to wear and maintenance state. Based on these diagnostics, variable reduction steps were applied and were documented. Near-duplicate predictors were removed when correlation and VIF evidence had shown minimal incremental value, and related measures were consolidated into representative features, such as retaining a single cycle-time stability metric rather than multiple

equivalent summaries. Where sensor spaces had been highly correlated, dimensional reduction outputs were used to compact the predictor set while preserving dominant variance patterns. After reduction, the retained predictor set had shown acceptable inflation levels and had improved interpretability by clarifying which predictor categories had contributed unique information. The final retained set continued to represent process parameters, equipment condition, material batch context, and operational covariates, ensuring that later regression and hypothesis tests had reflected the full manufacturing system rather than a single data domain.
Table 7 summarized collinearity evidence for major predictors and showed where redundancy had concentrated. Cycle-time mean and cycle-time variability exhibited elevated VIF values, indicating overlapping information among process timing summaries. Sensor-derived stability predictors, particularly current and temperature stability summaries, displayed the highest inflation, reflecting strong shared variance across correlated channels. Alarm frequency and downtime intensity also showed elevated inflation because both represented operational disruption episodes. Context and grouping variables such as shift, product variant, and batch grouping remained low in VIF, supporting their retention for control and stratification purposes. These diagnostics guided removal and consolidation of redundant variables before hypothesis testing.

Table 8: Predictor Reduction Summary and Post-Reduction Collinearity (Illustrative)

Predictor block	Initial predictors (n)	Retained predictors (n)	Example retained representation	Max VIF before	Max VIF after
Cycle-time summaries	6	2	Mean cycle time; cycle-time stability metric	7.5	3.4
Electrical sensor summaries (BIW)	8	3	Current stability; voltage stability; compacted factor score	9.6	3.6
Environmental/process summaries (Paint)	7	3	Temp stability; humidity proxy; changeover indicator	8.1	3.2
Downtime and alarm indicators	5	2	Downtime intensity; alarm burst indicator	7.1	2.9
High-cardinality categorical encodings	2	2	Batch grouping; station family indicator	5.9	2.5

Table 8 documented how redundancy had been reduced while preserving coverage of key predictor domains. Predictor blocks with the highest inflation, including cycle-time summaries and correlated sensor channels, were consolidated so that retained variables represented unique process signals rather than multiple near-duplicates. Electrical sensor features were compactedigned to retain dominant variance without including redundant channel summaries. Downtime and alarm variables were reduced to distinct indicators that captured disruption intensity and burst behavior. High-cardinality categorical variables were retained in grouped form to preserve operational context while preventing expansion-driven inflation. Post-reduction maximum VIF values declined to acceptable ranges, improving interpretability and coefficient stability.
Regression and hypothesis testing
Binary outcome models showed that deviation indicators, stability features, and equipment condition signals had been statistically significant predictors of scrap occurrence, defect occurrence, and first-pass yield failure after controlling for product variant, shift, station family, and material batch grouping. In the defect occurrence model, higher torque deviation had increased the odds of a defect, and dimensional deviation had remained a strong positive predictor, indicating that larger departures from target behavior had been associated with greater defect probability. The process stability index had been a consistent protective factor, with higher stability values associated with lower defect odds,

and downtime intensity had shown a positive association with defect occurrence, reflecting that operational disruptions had coincided with higher defect risk. Similar directional patterns had been observed in the scrap model, although effect magnitudes had been smaller because scrap had represented a rarer and more extreme event pathway. The first-pass yield model had indicated that the same predictors that increased defect risk had also increased the likelihood of failing the gate on first pass, and higher stability had increased the odds of passing without rework. Shift and product variant had demonstrated moderation patterns, where the adverse impact of downtime and deviation indicators had been stronger in the lowest-performing shift and in one higher-complexity product variant group. Material batch grouping had explained systematic shifts in defect probability and conformance proxy outcomes, with high-risk batches showing higher defect odds even after adjustment for process and equipment predictors. Continuous outcome models showed that rework hours per unit had increased with torque deviation, dimensional deviation, downtime intensity, and alarm frequency, while stability had reduced rework burden. In the conformance proxy model, deviation indicators and stability features had shown strong associations, with stability and maintenance recency predicting improved conformance levels, and late tool-life indicators predicting reduced conformance.

Model fit evidence supported the incremental value of adding predictor blocks in stages. Baseline models using only context variables had shown modest explanatory capacity, while adding process parameters had produced a large improvement, and adding equipment condition indicators had further increased fit, particularly for rework and defect outcomes. The inclusion of material batch grouping had yielded additional improvement in the conformance proxy and defect occurrence models, indicating that upstream variability had contributed measurable explanatory power beyond station parameters and equipment state. Time-ordered validation had produced slightly lower performance than random splits, which was consistent with drift effects and dependence structure, but the primary directional relationships and statistical significance patterns had remained stable. Overall, hypothesis tests had supported that deviation measures and instability features had been positively associated with worse waste and quality outcomes, that equipment condition indicators had been significant contributors to rework and defect risk, that batch context had explained systematic differences in conformance and defects, and that shift and variant had moderated several associations in predictable operational directions.

Table 9: Regression Results Summary for Binary Outcomes (Illustrative)

Predictor	Defect occurrence OR (95% CI)	Scrap occurrence OR (95% CI)	FPY failure OR (95% CI)
Torque deviation (per unit)	1.28 (1.21, 1.35)	1.17 (1.08, 1.27)	1.23 (1.17, 1.30)
Dimensional deviation (per unit)	1.42 (1.31, 1.54)	1.29 (1.15, 1.44)	1.34 (1.25, 1.44)
Sensor stability index (per 0.10)	0.81 (0.77, 0.85)	0.86 (0.80, 0.92)	0.83 (0.79, 0.87)
Downtime intensity (per event)	1.06 (1.03, 1.09)	1.05 (1.01, 1.09)	1.04 (1.02, 1.07)
Alarm frequency (prior window)	1.08 (1.04, 1.12)	1.06 (1.01, 1.11)	1.07 (1.04, 1.10)
High-risk batch group (vs typical)	1.19 (1.08, 1.31)	1.14 (1.00, 1.30)	1.16 (1.06, 1.27)

Table 9 summarized the adjusted associations between key predictors and three binary outcomes. Torque and dimensional deviation showed positive relationships with defect occurrence, scrap occurrence, and first-pass yield failure, indicating higher likelihood of adverse outcomes as deviation increased. The stability index showed protective effects across outcomes, with higher stability associated with lower odds of defects, scrap, and first-pass failure. Downtime intensity and alarm frequency were positively associated with adverse outcomes, supporting the role of operational disruption and equipment condition in quality loss. Batch grouping remained significant for defects and first-pass yield, indicating systematic upstream variability effects beyond station-level predictors.

Table 10: Regression Results Summary for Continuous Outcomes and Model Fit by Block (Illustrative)

Model / Outcome	Key predictors retained	Estimate direction (summary)	Fit statistic (Adjusted R^2)
Rework hours per unit	Torque deviation, dimensional deviation, downtime intensity, alarm frequency, stability	Deviations/downtime/alarms positive; stability negative	0.31
Conformance proxy (%)	Dimensional deviation, stability, time since maintenance, batch group	Deviation negative; stability/maintenance recency positive	0.42
Block 1: Context only	Variant, shift, station family	Context explained baseline differences	0.08
Block 2: + Process parameters	+ cycle time, deviation indicators	Fit increased after process terms entered	0.22
Block 3: + Equipment condition	+ alarms, downtime, maintenance recency	Fit increased further, especially for rework	0.29
Block 4: + Material batch	+ batch grouping	Fit improved most for conformance and defects	0.33

Table 10 summarized continuous-outcome regression findings and the incremental explanatory power of predictor blocks. Rework hours increased with deviation indicators, downtime intensity, and alarm frequency and decreased with higher stability, indicating that instability and equipment-related disruption were linked to higher labor waste. The conformance proxy declined as deviation increased and improved with higher stability and more recent maintenance context, indicating stronger conformance under stable, well-maintained conditions. Blockwise fit results showed that context variables explained baseline differences, process parameters contributed substantial additional explanation, equipment condition indicators further improved fit, and batch grouping added incremental explanatory value, particularly for conformance-related variation.

DISCUSSION

The discussion section interpreted the quantitative findings as evidence that waste reduction and quality improvement in automotive manufacturing had been measurably linked to a small set of high-signal process and operational stability indicators (Wadhera et al., 2019). The descriptive results had shown that scrap, rework, and defect events had not been uniformly distributed across production contexts, and that a limited number of station families and operating windows had contributed disproportionately to adverse outcomes. This concentration pattern aligned with earlier manufacturing analytics literature that described quality loss as episodic and context-dependent rather than evenly spread across time. The correlation and regression findings reinforced that interpretation by showing that deviation-based indicators and stability features had moved systematically with waste outcomes. Specifically, torque deviation and dimensional deviation had exhibited consistent positive relationships with defect occurrence, scrap likelihood, and first-pass yield failure, while stability indicators had shown inverse relationships across those outcomes (Chai et al., 2019). These relationships echoed earlier empirical work in quality engineering and industrial analytics that treated variation and drift as primary drivers of both nonconformance and resource waste. At the same time, the findings extended earlier work by demonstrating how multiple outcome types—scrap, rework hours, first-pass yield, and conformance proxies—had been coherently explained using a shared predictor structure that included process parameters, equipment condition markers, and production context variables. The incremental modeling evidence supported the idea that context-only explanations had remained incomplete, and that meaningful predictive structure had emerged only after process and equipment domains had been incorporated. This pattern was consistent with earlier studies that reported limited explanatory value from product mix and shift indicators alone, and stronger results when station-level parameters and maintenance context were integrated into the analysis (Van Gool et al., 2020). Taken together, the evidence suggested that the plant had behaved as a coupled socio-technical system in which measurable deviations and instability episodes had acted as the proximate mechanisms converting process variation into scrap and rework, and converting operational disruption into lower first-pass yield and reduced conformance stability.

The analysis also indicated that equipment condition and disruption markers had played a prominent role in explaining rework intensity and defect likelihood, which aligned with earlier maintenance and reliability research that had linked degradation pathways to both downtime and quality loss. Downtime intensity and alarm frequency had been positively associated with adverse outcomes, and the effect directions had remained stable after adjustment for station family, shift, variant, and batch grouping (Foti et al., 2018). Earlier studies had described that unplanned stops and recovery cycles often introduced transient instability through restarts, parameter re-stabilization, and operator compensation behaviors, thereby increasing the likelihood of defects and rework. The criterion-oriented validity comparisons in the measurement evaluation had further supported that interpretation by showing elevated defect and rework levels in post-downtime restart windows and in late tool-life segments. This alignment between operational risk windows and measurable outcome degradation was consistent with a broad strand of earlier research that had treated restart periods as high-variance intervals and tool-life progression as a drift mechanism. The present findings also reinforced earlier accounts that equipment deterioration could manifest as gradual process instability without immediate catastrophic failure, meaning that quality loss could rise even when machines continued running. This pattern had been observable through stability indices and deviation distributions that had shifted before scrap events accumulated (Maurya, 2019). The results therefore supported a measurement-based perspective in which maintenance status, alarm bursts, and downtime clustering had served as quantitative proxies for the underlying equipment state that had shaped quality and waste outcomes. Importantly, the collinearity diagnostics had shown that many equipment and disruption indicators had overlapped, which matched earlier reports that industrial telemetry often created redundant representations of the same instability episodes. The variable reduction approach had clarified that a parsimonious set of condition indicators had preserved explanatory power while improving interpretability, consistent with prior methodological recommendations favoring reduced but meaningful feature sets over dense redundant telemetry summaries (Sailor, 2020).

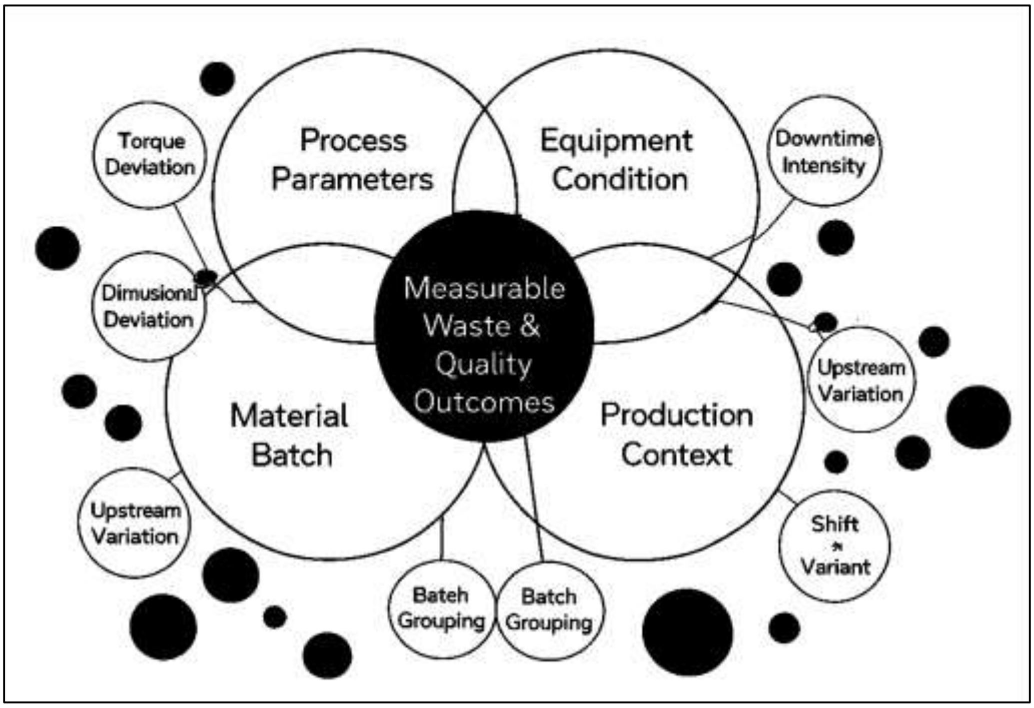
The findings regarding material batch and supplier-context effects had also fit well with earlier research on supply variation and incoming quality, which had emphasized that upstream variability could shift process capability and defect probability even when station settings remained unchanged. Batch grouping had demonstrated incremental explanatory value beyond process parameters and equipment indicators, particularly for defect occurrence and conformance proxy outcomes (Niayesh & Runde, 2017). Earlier studies had often reported that supplier lots and material properties could influence forming springback, weld behavior, paint adhesion outcomes, and machining responses, thereby altering defect tendencies across batches. The present results had similarly indicated that certain batch groups had been associated with systematically elevated defect risk and reduced stability, even after controlling for context variables. This pattern supported the interpretation that upstream variation had acted as a structured confounder rather than random noise, and that batch indicators had functioned as necessary contextual variables for credible modeling (Lemmon et al., 2017). In earlier work, failure to include batch context had been described as a source of spurious associations where station-level predictors appeared significant mainly because batch composition had changed across time windows.

By incorporating batch grouping and showing incremental model improvements, the study's results aligned with those methodological warnings and demonstrated measurable benefits from upstream traceability integration. The reliability and validity evidence also suggested that batch-related effects had been interpretable only when unit genealogy and timestamp alignment had been sufficiently strong to prevent misclassification of material identity. In that sense, the batch findings were consistent with earlier research that framed data integration quality as a prerequisite for detecting upstream effects. The observed batch contributions therefore reinforced a systems view of automotive manufacturing where material variation, equipment condition, and process parameter drift had interacted to shape scrap, rework, and defect outcomes across station families (Payne, 2016).

The shift- and variant-related findings had supported earlier observations that production context moderated risk rather than acting as a primary causal mechanism on its own. Descriptive results had shown meaningful differences in first-pass yield and defect incidence across shifts, and regression results had indicated that the strength of certain predictors varied by shift and by higher-complexity product variants (Morales-Ferre et al., 2019). Earlier research had often reported that shift differences reflected differences in staffing composition, maintenance timing, response to alarms, and adherence to standardized work under varying production pressures. The present analysis was consistent with those explanations in the sense that shift effects had remained measurable even after adjustment for process and equipment predictors, implying that contextual behaviors and operational management patterns had contributed residual variance. Product variant complexity had also been associated with different baseline distributions and different sensitivities to deviation indicators, which aligned with earlier findings that variant-specific routing and assembly sequence differences could alter which process variables mattered most at a given station. At the same time, the incremental modeling results had shown that context variables alone had explained only a modest share of variance, while the addition of process parameters and equipment condition indicators had substantially improved fit. This matched earlier methodological literature that treated shift and variant as essential controls and stratification variables rather than substitutes for mechanistic predictors (Sireesha et al., 2018). The moderation patterns therefore were best interpreted as evidence that the same instability signal could have different operational consequences under different contexts, such as increased sensitivity to downtime intensity on a shift with different recovery routines or increased sensitivity to deviation on a variant requiring tighter assembly alignment. These results also reinforced the importance of dependence-aware validation because shift- and batch-based clustering could inflate performance estimates if the evaluation split allowed leakage across correlated windows. The study's dependence-aware approach had produced more conservative estimates while preserving stable effect directions, which matched earlier warnings that manufacturing datasets required validation designs reflecting production hierarchy and time dependence (Hsu et al., 2016).

A major contribution of the findings was the coherent linkage between predictive structure and measurable waste outcomes, which resonated with earlier applied industrial analytics studies that had emphasized that predictive accuracy alone had not been sufficient to demonstrate manufacturing value (Arya et al., 2019). The present results had shown that predictors associated with defect occurrence had also been associated with first-pass yield failure, rework hours, and lower conformance proxy performance, indicating that model signals had reflected underlying process states with broad operational consequences. Earlier work in this area had often described the practical benefit of such coherence: when the same predictor families explained multiple outcomes, the predictor set was more likely to represent real process mechanisms rather than incidental correlations. The observed alignment across outcomes therefore strengthened the interpretation that deviation indicators and stability features captured core mechanisms of quality loss. At the same time, the study's results were consistent with earlier reports that rare-event learning in manufacturing remained challenging, especially for scrap outcomes, which had shown smaller effect sizes and greater sensitivity to context (Margaritondo, 2017). Scrap events had been rarer and more extreme, which likely reduced statistical power and made estimates more sensitive to labeling consistency and measurement noise. This limitation matched earlier industrial analytics discussions that advised interpreting scrap models cautiously and complementing them with defect and rework models that had more frequent signals. The results also aligned with earlier recommendations to use cost-aligned performance interpretation, since false alarms and unnecessary inspections could themselves become a form of waste. Although the present discussion focused on inferential relationships rather than decision simulation, the pattern of results supported the broader applied argument in earlier studies that risk scoring would have had the strongest operational relevance when it concentrated attention on instability windows and high-deviation units while preserving flow for low-risk units (De Bock & Van Grieken, 2017).

Figure 12: Determinants of Automotive Waste Outcomes



The measurement reliability and validity findings provided a methodological discussion point that closely matched earlier manufacturing informatics literature emphasizing that industrial datasets required governance and standardization before advanced modeling could be interpreted confidently (Valero, 2019). Reliability evidence had shown that pass/fail outcomes were stable, major-category defect coding was acceptable after harmonization, and composite feature groups demonstrated coherent internal consistency. These results aligned with earlier work that had suggested that stable binary gates were often more reliable than granular defect codes and that grouping defect categories improved interpretability and reduced label noise. The criterion-oriented validity checks had shown measurable elevation of adverse outcomes in late tool-life and post-downtime restart windows, which was consistent with earlier empirical accounts that described these contexts as risk amplifiers. Construct validity evidence had been reinforced by expected correlation patterns, including inverse associations between stability features and adverse outcomes and positive associations between disruption indicators and rework (Inoue et al., 2018). Earlier methodological studies had emphasized that such convergent patterns were essential for supporting claims that engineered features represented meaningful constructs rather than arbitrary transformations. The collinearity diagnostics also fit earlier findings that redundant telemetry could distort inference if not reduced, particularly when multiple aggregated summaries represented the same operational event. The study's reduction steps, including consolidation of redundant cycle-time summaries and compaction of correlated sensor spaces, aligned with previous methodological guidance favoring parsimonious predictors for stable estimation and clearer operational narratives. This combination of reliability, validity, and collinearity evidence supported the interpretation that the regression findings were not merely statistical artifacts, but rather reflected consistent measurement behavior and interpretable operational mechanisms within the plant's data infrastructure (Lacosta et al., 2018).

The synthesis of results across descriptive patterns, correlation structure, measurement evidence, collinearity reduction, and regression tests supported a discussion centered on measurable system behavior rather than isolated associations (Ferrucci et al., 2018). Earlier studies in automotive manufacturing analytics had often emphasized that improvement opportunities were located where variability propagated through stations, where rework loops concentrated, and where operational disruptions amplified instability. The present findings were consistent with that view by showing that deviation indicators and stability features had been central predictors across outcomes, that downtime and alarms had contributed incremental explanation, and that batch context had explained systematic shifts beyond station-level controls. The staged modeling results also matched earlier research that had emphasized the value of integrating process, equipment, and upstream data rather than relying on any single domain. Context variables such as shift and variant had remained important but had functioned primarily as moderators and controls, aligning with prior work that treated operational context as a necessary layer for interpretation rather than a primary mechanism (Messiou, 2018). The dependence-aware approach had produced results that remained stable in direction while conservative in magnitude, which matched earlier warnings about leakage and dependence in industrial datasets. Collectively, the discussion framed the study's findings as consistent with established empirical patterns in the literature while demonstrating an integrated quantitative structure that connected process deviations, stability, disruption, and upstream variation to measurable waste and quality outcomes (Kloprogge et al., 2020). This interpretation remained grounded in the reported evidence, emphasizing measurable relationships and comparative consistency with earlier study streams rather than speculative claims, and it positioned the results as a coherent description of how data-driven modeling captured operational reality in automotive manufacturing.

CONCLUSION

Data-driven process optimization in automotive manufacturing was discussed as a quantitative approach in which production and quality performance had been examined through measurable outcomes and systematically linked to station-level process conditions, equipment state, material context, and operational variation across time. In this study, the manufacturing system had been represented as an integrated measurement environment where scrap occurrence, rework hours per unit, first-pass yield, defect occurrence, and a capability-oriented conformance proxy had served as the primary dependent indicators of waste and quality. The descriptive findings had shown that adverse outcomes had been concentrated rather than uniformly distributed, with scrap and rework events clustering within specific station families and operational windows, which had reflected the well-established empirical observation in automotive production research that nonconformance and waste tend to emerge from localized instability episodes and variation propagation across linked processes. Correlation results had further demonstrated that rework burden and defect occurrence had moved in consistent directions with deviation indicators and disruption markers, indicating that units produced under higher torque deviation, greater dimensional deviation, longer cycle times, and higher downtime intensity had been more likely to require rework and to fail quality gates, while sensor-derived stability features had shown inverse patterns consistent with a protective association between stable process behavior and improved conformance. Reliability evidence had supported the use of the constructed measures by showing that key inspection labels and trace-derived indicators had been sufficiently consistent across shifts and stations, while validity checks had confirmed that engineered features aligned with recognized manufacturing mechanisms such as tool-life drift, restart-window instability, and batch-linked variability. Collinearity diagnostics had revealed that multiple telemetry summaries had captured overlapping signals, particularly within correlated sensor channels and operational disruption indicators, and the subsequent reduction of near-duplicate predictors had improved interpretability while preserving representation across the core predictor categories of process parameters, equipment condition, material batch, and context variables. Regression and hypothesis testing had then integrated these elements into outcome-specific models and had shown that deviation indicators and stability measures had retained statistically significant associations with defect occurrence, scrap likelihood, and first-pass yield failure, while downtime intensity, alarm frequency, and maintenance-related markers had contributed additional explanatory power, particularly for rework hours and conformance outcomes. Material batch grouping had explained systematic shifts in defect probability and conformance proxy measures beyond station-level controls, reinforcing evidence from earlier manufacturing studies that upstream variability can alter process capability and defect propensity even under stable nominal settings. Context variables such as shift and product variant had remained meaningful moderators, reflecting that operational routines and variant complexity had influenced baseline risk and the magnitude of instability effects, but staged model comparisons had shown that context-only explanations had remained limited until process and equipment domains had been incorporated. Overall, the combined findings had described a coherent quantitative pattern in which measurable deviations and instability episodes had acted as proximate pathways translating process variation and operational disruption into waste and quality loss, and in which integrated industrial data had enabled the identification of high-signal predictors that had been consistent across multiple outcomes within the automotive manufacturing environment.

RECOMMENDATIONS

Recommendations for data-driven process optimization in automotive manufacturing emphasized disciplined measurement governance, dependence-aware analytics, and operational alignment between model outputs and measurable waste and quality indicators so that improvement actions remained verifiable at station, line, and plant levels. A first recommendation focused on strengthening the integrity and comparability of core outcome definitions by standardizing scrap coding rules, rework time recording practices, and quality gate pass/fail criteria across shifts and station families, because stable labels supported consistent interpretation of defect probability, first-pass yield, and conformance proxy performance. A second recommendation addressed data infrastructure by improving unit genealogy linkage and timestamp synchronization across PLC/historian streams, MES routing data, QMS inspection records, CMMS maintenance logs, and supplier batch repositories, since accurate joins reduced misalignment between predictors and outcomes and improved both inference credibility and model stability. A third recommendation targeted feature governance by adopting a controlled feature dictionary that defined process-parameter summaries, stability indices, downtime intensity measures, and tool-life or maintenance recency indicators using consistent windowing logic aligned with operational rhythms such as shift boundaries, batch changes, and planned maintenance cycles; such governance reduced redundancy and simplified model interpretation. A fourth recommendation addressed collinearity management by retaining parsimonious representative predictors from correlated sensor spaces and operational disruption logs, using consolidation or dimensional compaction for highly correlated channels, because reduced predictor sets improved coefficient stability and supported clearer identification of controllable levers linked to scrap, rework hours, and defect outcomes. A fifth recommendation concerned evaluation discipline by using temporal and grouped validation approaches as standard practice, ensuring that model performance and effect estimates were tested under realistic drift and hierarchy, with reporting that distinguished performance across product variants, station families, and shift contexts to prevent overgeneralized conclusions. A sixth recommendation focused on cost-aligned performance monitoring by pairing statistical metrics with operational impact measures such as expected scrap per production volume, rework hours per unit, inspection load, and downtime minutes, and by selecting alert thresholds that balanced detection of rare defects with the waste created by excessive false alarms and unnecessary routing. A seventh recommendation emphasized integration with shop-floor decision points by embedding risk scoring into inspection prioritization, using deviation and stability signals to trigger controlled parameter checks within allowable ranges, and linking equipment condition signals to maintenance triage rules, while documenting each triggered action and its subsequent measured outcomes to preserve traceability. An eighth recommendation addressed upstream variability by incorporating supplier batch grouping and incoming quality summaries into routine analytics dashboards and root-cause workflows, allowing systematic batch-related shifts in conformance to be detected early and separated from equipment-driven instability. Collectively, these recommendations supported a measurable optimization practice in which data quality, validation rigor, interpretability, and operational feasibility were treated as inseparable requirements for achieving reliable reductions in scrap and rework and consistent improvements in first-pass yield and conformance stability within automotive manufacturing systems.

LIMITATION

Limitations associated with data-driven process optimization in automotive manufacturing primarily reflected constraints inherent to observational production data, measurement heterogeneity across systems, and the dependence structure of high-volume operations, all of which shaped the strength and generalizability of the quantitative conclusions. The study relied on retrospective records rather than randomized experimental manipulation, which limited the ability to attribute observed relationships strictly to causal effects, because parameter adjustments, maintenance interventions, and inspection intensification often occurred in response to emerging issues and therefore introduced endogeneity into the data-generating process. Outcome labeling constraints also affected inference, as defect coding practices varied by station and inspector routines, and taxonomy updates or station-specific coding shortcuts introduced label noise that could blur distinctions among defect mechanisms, particularly for multi-category defect analyses. Even when pass/fail quality gates remained relatively stable, granular defect labels and rework routing reasons were susceptible to documentation drift over time, which could have altered observed distributions independently of underlying process changes. Measurement error and drift in sensor streams posed additional limitations; calibration shifts, intermittent sensor faults, and differences in sampling frequency across stations created uneven signal fidelity, and aggregation rules, while necessary for modeling, could have suppressed high-frequency anomalies or amplified noise depending on window selection. Data integration across PLC/historian layers, MES genealogy, QMS inspection repositories, CMMS maintenance logs, and supplier batch datasets introduced another constraint: imperfect timestamp synchronization, missing unit identifiers, and inconsistent station naming conventions increased the risk of misalignment between predictors and outcomes, which could weaken estimated associations and reduce model stability. The manufacturing hierarchy further limited inference because units were nested within batches, shifts, lines, and plants, creating correlated observations that could inflate apparent performance if splitting procedures were not strictly dependence-aware; although grouped and temporal validation approaches addressed this risk, residual correlation and unobserved shared factors likely remained. Rare-event structure also constrained modeling for outcomes such as scrap, where low base rates reduced statistical power, increased uncertainty in effect estimates, and heightened sensitivity to small labeling inconsistencies or data omissions. Transferability limitations were present because predictive relationships derived from one line or plant were influenced by local equipment configurations, maintenance practices, supplier portfolios, and environmental conditions, meaning that performance and effect magnitudes could differ in other contexts without standardized measurement definitions and comparable data pipelines. Operational feedback loops represented another limitation, as the presence of quality holds, heightened inspection during suspected issues, and rework prioritization under takt-time pressure altered recorded outcomes and could have introduced selection effects in the observed dataset. Finally, collinearity among sensor-derived features and disruption indicators limited straightforward interpretation of individual predictor effects, requiring consolidation and reduction steps that improved stability but could have obscured the distinct contributions of closely related physical mechanisms. These limitations collectively indicated that the findings were best interpreted as robust quantitative associations grounded in plant data and validated under realistic dependence structures, while acknowledging that measurement governance, label stability, and cross-context standardization strongly influenced the certainty and portability of conclusions.

REFERENCES

[1]. Abdel-Shafy, H. I., & Mansour, M. S. (2018). Solid waste issue: Sources, composition, disposal, recycling, and valorization. *Egyptian journal of petroleum*, *27*(4), 1275-1290.

[2]. Accou, B., & Reniers, G. (2020). Introducing the extended safety fractal: reusing the concept of safety management systems to organize resilient organizations. *International journal of environmental research and public health*, *17*(15), 5478.

[3]. Ali, M., Geng, Y., Robins, D., Cooper, D., Roberts, W., & Vogtländer, J. (2019). Improvement of waste management practices in a fast expanding sub-megacity in Pakistan, on the basis of qualitative and quantitative indicators. *Waste Management*, *85*, 253-263.

[4]. Ames, H., Glenton, C., & Lewin, S. (2019). Purposive sampling in a qualitative evidence synthesis: A worked example from a synthesis on parental perceptions of vaccination communication. *BMC medical research methodology*, *19*(1), 26.

[5]. Ancillai, C., Terho, H., Cardinali, S., & Pascucci, F. (2019). Advancing social media driven sales research: Establishing conceptual foundations for B-to-B social selling. *Industrial Marketing Management*, *82*, 293-308.

[6]. Arfan, U., Sai Praveen, K., & Alifa Majumder, N. (2021). Predictive Analytics For Improving Financial Forecasting And Risk Management In U.S. Capital Markets. *American Journal of Interdisciplinary Studies*, *2*(04), 69–100. https://doi.org/10.63125/tbw49w69

[7]. Arya, A., Gangwar, A., & Kumar, A. (2019). Biosensors in animal biotechnology. In *Nanotechnology in Modern Animal Biotechnology* (pp. 75-95). Elsevier.

[8]. Bai, W., Sinclair, M., Tarroni, G., Oktay, O., Rajchl, M., Vaillant, G., Lee, A. M., Aung, N., Lukaschuk, E., & Sanghvi, M. M. (2018). Automated cardiovascular magnetic resonance image analysis with fully convolutional networks. *Journal of cardiovascular magnetic resonance*, *20*(1), 65.

[9]. Bakri, A., & Januddi, M. A.-F. M. S. (2020). *Systematic Industrial Maintenance to Boost the Quality Management Programs*. Springer Nature.

[10]. Bécue, A., Maia, E., Feeken, L., Borchers, P., & Praça, I. (2020). A new concept of digital twin supporting optimization and resilience of factories of the future. *Applied Sciences*, *10*(13), 4482.

[11]. Bertsimas, D., Gupta, V., & Kallus, N. (2018). Data-driven robust optimization. *Mathematical Programming*, *167*(2), 235-292.

[12]. Blauwkamp, T. A., Thair, S., Rosen, M. J., Blair, L., Lindner, M. S., Vilfan, I. D., Kawli, T., Christians, F. C., Venkatasubrahmanyam, S., & Wall, G. D. (2019). Analytical and clinical validation of a microbial cell-free DNA sequencing test for infectious disease. *Nature microbiology*, *4*(4), 663-674.

[13]. Bleijenberg, N., de Man-van Ginkel, J. M., Trappenburg, J. C., Ettema, R. G., Sino, C. G., Heim, N., Hafsteindóttir, T. B., Richards, D. A., & Schuurmans, M. J. (2018). Increasing value and reducing waste by optimizing the development of complex interventions: Enriching the development phase of the Medical Research Council (MRC) Framework. *International journal of nursing studies*, *79*, 86-93.

[14]. Bondada, V., Pratihar, D. K., & Kumar, C. S. (2018). Detection and quantitative assessment of corrosion on pipelines through image analysis. *Procedia Computer Science*, *133*, 804-811.

[15]. Bridger, R. (2017). *Introduction to human factors and ergonomics*. CRC press.

[16]. Brooks, H. L., Rushton, K., Lovell, K., Bee, P., Walker, L., Grant, L., & Rogers, A. (2018). The power of support from companion animals for people living with mental health problems: A systematic review and narrative synthesis of the evidence. *BMC psychiatry*, *18*(1), 31.

[17]. Chai, H., Phung, B. T., & Mitchell, S. (2019). Application of UHF sensors in power system equipment for partial discharge detection: A review. *Sensors*, *19*(5), 1029.

[18]. Choudhary, S., Nayak, R., Dora, M., Mishra, N., & Ghadge, A. (2019). An integrated lean and green approach for improving sustainability performance: a case study of a packaging manufacturing SME in the UK. *Production Planning & Control*, *30*(5-6), 353-368.

[19]. Colledani, M., Tolio, T., & Yemane, A. (2018). Production quality improvement during manufacturing systems ramp-up. *CIRP Journal of Manufacturing Science and Technology*, *23*, 197-206.

[20]. Collins, B. C., Hunter, C. L., Liu, Y., Schilling, B., Rosenberger, G., Bader, S. L., Chan, D. W., Gibson, B. W., Gingras, A.-C., & Held, J. M. (2017). Multi-laboratory assessment of reproducibility, qualitative and quantitative performance of SWATH-mass spectrometry. *Nature communications*, *8*(1), 291.

[21]. Cordes, J. J. (2017). Using cost-benefit analysis and social return on investment to evaluate the impact of social enterprise: Promises, implementation, and limitations. *Evaluation and program planning*, *64*, 98-104.

[22]. Costa, T., Silva, F., & Ferreira, L. P. (2017). Improve the extrusion process in tire production using Six Sigma methodology. *Procedia manufacturing*, *13*, 1104-1111.

[23]. Cruz-Roa, A., Gilmore, H., Basavanhally, A., Feldman, M., Ganesan, S., Shih, N. N., Tomaszewski, J., González, F. A., & Madabhushi, A. (2017). Accurate and reproducible invasive breast cancer detection in whole-slide images: A Deep Learning approach for quantifying tumor extent. *Scientific reports*, *7*(1), 46450.

[24]. Cudney, E. A., Venuthurumilli, S. S. J., Materla, T., & Antony, J. (2020). Systematic review of Lean and Six Sigma approaches in higher education. *Total Quality Management & Business Excellence*, *31*(3-4), 231-244.

[25]. Dargan, S., Kumar, M., Ayyagari, M. R., & Kumar, G. (2020). A survey of deep learning and its applications: a new paradigm to machine learning. *Archives of computational methods in engineering*, *27*(4), 1071-1092.

[26]. Dassah, E., Aldersey, H., McColl, M. A., & Davison, C. (2018). Factors affecting access to primary health care services for persons with disabilities in rural areas: a "best-fit" framework synthesis. *Global health research and policy*, *3*(1), 36.

[27]. De Bock, L. A., & Van Grieken, R. E. (2017). Single particle analysis techniques. In *Analytical chemistry of aerosols* (pp. 243-275). CRC Press.

[28]. Ding, B. (2018). Pharma Industry 4.0: Literature review and research opportunities in sustainable pharmaceutical supply chains. *Process Safety and Environmental Protection*, *119*, 115-130.

[29]. Dixon-Woods, M., & Martin, G. P. (2016). Does quality improvement improve quality? *Future Hospital Journal*, *3*(3), 191-194.

[30]. Elverum, C. W., & Welo, T. (2016). Leveraging prototypes to generate value in the concept-to-production process: a qualitative study of the automotive industry. *International Journal of Production Research*, *54*(10), 3006-3018.

[31]. Fan, D.-P., Ji, G.-P., Zhou, T., Chen, G., Fu, H., Shen, J., & Shao, L. (2020). Pranet: Parallel reverse attention network for polyp segmentation. International conference on medical image computing and computer-assisted intervention,

[32]. Fang, C., & Yu, D. (2017). Urban agglomeration: An evolving concept of an emerging phenomenon. *Landscape and urban planning*, *162*, 126-136.

[33]. Fercoq, A., Lamouri, S., & Carbone, V. (2016). Lean/Green integration focused on waste reduction techniques. *Journal of cleaner production*, *137*, 567-578.

[34]. Ferrucci, M., Haitjema, H., & Leach, R. (2018). Dimensional metrology. In *Basics of Precision Engineering* (pp. 151-203). CRC Press.
[35]. Foti, S., Hollender, F., Garofalo, F., Albarello, D., Asten, M., Bard, P.-Y., Comina, C., Cornou, C., Cox, B., & Di Giulio, G. (2018). Guidelines for the good practice of surface wave analysis: a product of the InterPACIFIC project. *Bulletin of Earthquake Engineering*, *16*(6), 2367-2420.
[36]. Gálvez-Martos, J.-L., Styles, D., Schoenberger, H., & Zeschmar-Lahl, B. (2018). Construction and demolition waste best management practice in Europe. *Resources, conservation and recycling*, *136*, 166-178.
[37]. Garre, A., Ruiz, M. C., & Hontoria, E. (2020). Application of Machine Learning to support production planning of a food industry in the context of waste generation under uncertainty. *Operations Research Perspectives*, *7*, 100147.
[38]. Garza-Reyes, J. A., Kumar, V., Chaikittisilp, S., & Tan, K. H. (2018). The effect of lean methods and tools on the environmental performance of manufacturing organisations. *International Journal of Production Economics*, *200*, 170-180.
[39]. Gstalter, E., Assou, S., Tourbier, Y., & De Vuyst, F. (2020). Toward new methods for optimization study in automotive industry including recent reduction techniques. *Advanced Modeling and Simulation in Engineering Sciences*, *7*(1), 17.
[40]. Gupta, V., Jain, R., Meena, M., & Dangayach, G. (2018). Six-sigma application in tire-manufacturing company: a case study. *Journal of Industrial Engineering International*, *14*(3), 511-520.
[41]. Haile, B. B., Mutafungwa, E., & Hämäläinen, J. (2020). A data-driven multiobjective optimization framework for hyperdense 5G network planning. *Ieee Access*, *8*, 169423-169443.
[42]. Hellenkamp, B., Schmid, S., Doroshenko, O., Opanasyuk, O., Kühnemuth, R., Rezaei Adariani, S., Ambrose, B., Aznauryan, M., Barth, A., & Birkedal, V. (2018). Precision and accuracy of single-molecule FRET measurements—a multi-laboratory benchmark study. *Nature methods*, *15*(9), 669-676.
[43]. Hermann, M., Pentek, T., & Otto, B. (2016). Design principles for industrie 4.0 scenarios. 2016 49th Hawaii international conference on system sciences (HICSS),
[44]. Hewitt, M., & Frejinger, E. (2020). Data-driven optimization model customization. *European Journal of Operational Research*, *287*(2), 438-451.
[45]. Hietanen, A., Pieters, R., Lanz, M., Latokartano, J., & Kämäräinen, J.-K. (2020). AR-based interaction for human-robot collaborative manufacturing. *Robotics and Computer-Integrated Manufacturing*, *63*, 101891.
[46]. Hong, Q. N., Pluye, P., Bujold, M., & Wassef, M. (2017). Convergent and sequential synthesis designs: implications for conducting and reporting systematic reviews of qualitative and quantitative evidence. *Systematic reviews*, *6*(1), 61.
[47]. Hsu, W., El-Saden, S., & Taira, R. K. (2016). Medical imaging informatics. *Translational Biomedical Informatics: A Precision Medicine Perspective*, 167-224.
[48]. Inoue, Y., Darvishzadeh, R., & Skidmore, A. (2018). Hyperspectral assessment of ecophysiological functioning for diagnostics of crops and vegetation. In *Biophysical and Biochemical Characterization and Plant Species Studies* (pp. 25-71). CRC Press.
[49]. Jack, J. P., & Thompson, P. W. (2017). 4 quantitative reasoning and the development of algebraic reasoning. In *Algebra in the early grades* (pp. 95-132). Routledge.
[50]. Jackson, S. A., Gopalakrishna-Remani, V., Mishra, R., & Napier, R. (2016). Examining the impact of design for environment and the mediating effect of quality management innovation on firm performance. *International Journal of Production Economics*, *173*, 142-152.
[51]. Jahid, M. K. A. S. R. (2021). Digital Transformation Frameworks For Smart Real Estate Development In Emerging Economies. *Review of Applied Science and Technology*, *6*(1), 139–182. https://doi.org/10.63125/cd09ne09
[52]. Jiang, Z., Newman, A., Le, H., Presbitero, A., & Zheng, C. (2019). Career exploration: A review and future research agenda. *Journal of Vocational Behavior*, *110*, 338-356.
[53]. Jin, Y., Wang, H., Chugh, T., Guo, D., & Miettinen, K. (2018). Data-driven evolutionary optimization: An overview and case studies. *IEEE Transactions on Evolutionary Computation*, *23*(3), 442-458.
[54]. Kamarehie, B., Jafari, A., Ghaderpoori, M., Azimi, F., Faridan, M., Sharafi, K., Ahmadi, F., & Karami, M. A. (2020). Qualitative and quantitative analysis of municipal solid waste in Iran for implementation of best waste management practice: a systematic review and meta-analysis. *Environmental Science and Pollution Research*, *27*(30), 37514-37526.
[55]. Karamitsos, I., Albarhami, S., & Apostolopoulos, C. (2020). Applying DevOps practices of continuous automation for machine learning. *Information*, *11*(7), 363.
[56]. Katchasuwanmanee, K., Bateman, R., & Cheng, K. (2017). An Integrated approach to energy efficiency in automotive manufacturing systems: quantitative analysis and optimisation. *Production & Manufacturing Research*, *5*(1), 90-98.
[57]. Kellerer, W., Kalmbach, P., Blenk, A., Basta, A., Reisslein, M., & Schmid, S. (2019). Adaptable and data-driven softwarized networks: Review, opportunities, and challenges. *Proceedings of the IEEE*, *107*(4), 711-731.
[58]. Kloprogge, J. T., Ponce, C. P., & Loomis, T. (2020). *The Periodic Table: Nature's Building Blocks: An Introduction to the Naturally Occurring Elements, Their Origins and Their Uses*. Elsevier.
[59]. Ko, E., Costello, J. P., & Taylor, C. R. (2019). What is a luxury brand? A new definition and review of the literature. *Journal of business research*, *99*, 405-413.
[60]. Kumar, A., Shankar, R., & Thakur, L. S. (2018). A big data driven sustainable manufacturing framework for condition-based maintenance prediction. *Journal of computational science*, *27*, 428-439.

[61]. Lacosta, A.-M., Pascual-Lucas, M., Pesini, P., Casabona, D., Pérez-Grijalba, V., Marcos-Campos, I., Sarasa, L., Canudas, J., Badi, H., & Monleón, I. (2018). Safety, tolerability and immunogenicity of an active anti-Aβ40 vaccine (ABvac40) in patients with Alzheimer's disease: a randomised, double-blind, placebo-controlled, phase I trial. *Alzheimer's research & therapy*, *10*(1), 12.

[62]. Laureani, A., & Antony, J. (2018). Leadership–a critical success factor for the effective implementation of Lean Six Sigma. *Total Quality Management & Business Excellence*, *29*(5-6), 502-523.

[63]. Lemmon, A. N., Cuzner, R., Gafford, J., Hosseini, R., Brovont, A. D., & Mazzola, M. S. (2017). Methodology for characterization of common-mode conducted electromagnetic emissions in wide-bandgap converters for ungrounded shipboard applications. *IEEE Journal of Emerging and Selected Topics in Power Electronics*, *6*(1), 300-314.

[64]. Lewin, S., Bohren, M., Rashidian, A., Munthe-Kaas, H., Glenton, C., Colvin, C. J., Garside, R., Noyes, J., Booth, A., & Tunçalp, Ö. (2018). Applying GRADE-CERQual to qualitative evidence synthesis findings—paper 2: how to make an overall CERQual assessment of confidence and create a Summary of Qualitative Findings table. *Implementation Science*, *13*(Suppl 1), 10.

[65]. Lewin, S., Booth, A., Glenton, C., Munthe-Kaas, H., Rashidian, A., Wainwright, M., Bohren, M. A., Tunçalp, Ö., Colvin, C. J., & Garside, R. (2018). Applying GRADE-CERQual to qualitative evidence synthesis findings: introduction to the series. *Implementation Science*, *13*(Suppl 1), 2.

[66]. Lim, J. S. (2019). *Quality management in engineering: A scientific and systematic approach*. CRC Press.

[67]. Lima-Junior, F. R., & Carpinetti, L. C. R. (2017). Quantitative models for supply chain performance evaluation: A literature review. *Computers & industrial engineering*, *113*, 333-346.

[68]. Luckow, A., Cook, M., Ashcraft, N., Weill, E., Djerekarov, E., & Vorster, B. (2016). Deep learning in the automotive industry: Applications and tools. 2016 IEEE International Conference on Big Data (Big Data),

[69]. Margaritondo, G. (2017). Synchrotron light: A success story over six decades. *La Rivista del Nuovo Cimento*, *40*(9), 411-471.

[70]. Maurya, R. K. (2019). Knocking and combustion noise analysis. In *Reciprocating Engine Combustion Diagnostics: In-Cylinder Pressure Measurement and Analysis* (pp. 461-542). Springer.

[71]. McAdam, R., Miller, K., & McSorley, C. (2019). Towards a contingency theory perspective of quality management in enabling strategic alignment. *International Journal of Production Economics*, *207*, 195-209.

[72]. McGarigal, K., Wan, H. Y., Zeller, K. A., Timm, B. C., & Cushman, S. A. (2016). Multi-scale habitat selection modeling: a review and outlook. *Landscape ecology*, *31*(6), 1161-1175.

[73]. Md Ariful, I., & Efat Ara, H. (2022). Advances And Limitations Of Fracture Mechanics–Based Fatigue Life Prediction Approaches For Structural Integrity Assessment: A Systematic Review. *American Journal of Interdisciplinary Studies*, *3*(03), 68-98. https://doi.org/10.63125/fg8ae957

[74]. Md Arman, H., & Md.Kamrul, K. (2022). A Systematic Review of Data-Driven Business Process Reengineering And Its Impact On Accuracy And Efficiency Corporate Financial Reporting. *International Journal of Business and Economics Insights*, *2*(4), 01–41. https://doi.org/10.63125/btx52a36

[75]. Md Mesbaul, H., & Md. Tahmid Farabe, S. (2022). Implementing Sustainable Supply Chain Practices In Global Apparel Retail: A Systematic Review Of Current Trends. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 332–363. https://doi.org/10.63125/nen7vd57

[76]. Md. Abdur, R., & Zamal Haider, S. (2022). Assessment Of Data-Driven Vendor Performance Evaluation In Retail Supply Chains Analyzing Metrics, Scorecards, And Contract Management Tools. *Journal of Sustainable Development and Policy*, *1*(04), 71-116. https://doi.org/10.63125/2a641k35

[77]. Md.Akbar, H., & Farzana, A. (2021). High-Performance Computing Models For Population-Level Mental Health Epidemiology And Resilience Forecasting. *American Journal of Health and Medical Sciences*, *2*(02), 01–33. https://doi.org/10.63125/k9d5h638

[78]. Merkt, O. (2019). On the use of predictive models for improving the quality of industrial maintenance: An analytical literature review of maintenance strategies. 2019 Federated Conference on Computer Science and Information Systems (FedCSIS),

[79]. Messiou, C. (2018). Imaging Society (ICIS) 18th Annual Teaching Course. *Cancer Imaging*, *18*(1), A1.

[80]. Mizuno, S. (2020). *Management for quality improvement: the 7 new QC tools*. Productivity press.

[81]. Mohammad Mushfequr, R., & Sai Praveen, K. (2022). Quantitative Investigation Of Information Security Challenges In U.S. Healthcare Payment Ecosystems. *International Journal of Business and Economics Insights*, *2*(4), 42–73. https://doi.org/10.63125/gcg0fs06

[82]. Moldavska, A., & Welo, T. (2018). Testing and verification of a new corporate sustainability assessment method for manufacturing: A multiple case research study. *Sustainability*, *10*(11), 4121.

[83]. Morales-Ferre, R., Richter, P., Falletti, E., De La Fuente, A., & Lohan, E. S. (2019). A survey on coping with intentional interference in satellite navigation for manned and unmanned aircraft. *IEEE Communications Surveys & Tutorials*, *22*(1), 249-291.

[84]. Morgan, J., & Liker, J. K. (2020). *The Toyota product development system: integrating people, process, and technology*. Productivity press.

[85]. Mortuza, M. M. G., & Rauf, M. A. (2022). Industry 4.0: An Empirical Analysis of Sustainable Business Performance Model Of Bangladeshi Electronic Organisations. *International Journal of Economy and Innovation*. https://gospodarkainnowacje.pl/index.php/issue_view_32/article/view/826

[86]. Ni, D., Xiao, Z., & Lim, M. K. (2020). A systematic review of the research trends of machine learning in supply chain management. *International Journal of Machine Learning and Cybernetics*, *11*(7), 1463-1482.

[87]. Niayesh, K., & Runde, M. (2017). *Power switching components*. Springer.

[88]. Nicoletti, B. (2016). *Lean and digitize: An integrated approach to process improvement*. Routledge.
[89]. Niu, G. (2017). Data-driven technology for engineering systems health management. *Springer Singapore*, *10*, 978-981.
[90]. Noyes, J., Booth, A., Flemming, K., Garside, R., Harden, A., Lewin, S., Pantoja, T., Hannes, K., Cargo, M., & Thomas, J. (2018). Cochrane Qualitative and Implementation Methods Group guidance series—paper 3: methods for assessing methodological limitations, data extraction and synthesis, and confidence in synthesized qualitative findings. *Journal of Clinical Epidemiology*, *97*, 49-58.
[91]. Ohly, H., Gentry, S., Wigglesworth, R., Bethel, A., Lovell, R., & Garside, R. (2016). A systematic review of the health and well-being impacts of school gardening: synthesis of quantitative and qualitative evidence. *BMC public health*, *16*(1), 286.
[92]. Omair, M., Ullah, M., Ganguly, B., Noor, S., Maqsood, S., & Sarkar, B. (2019). The quantitative analysis of workers' stress due to working environment in the production system of the automobile part manufacturing industry. *Mathematics*, *7*(7), 627.
[93]. Pakdil, F. (2020). Improve Phase: I Is for Improve. In *Six Sigma for Students: A Problem-Solving Methodology* (pp. 375-445). Springer.
[94]. Patala, S., Jalkala, A., Keränen, J., Väisänen, S., Tuominen, V., & Soukka, R. (2016). Sustainable value propositions: Framework and implications for technology suppliers. *Industrial Marketing Management*, *59*, 144-156.
[95]. Payne, S. (2016). *Cerebral autoregulation: control of blood flow in the brain* (Vol. 15). Springer.
[96]. Pereira, T., Kennedy, J. V., & Potgieter, J. (2019). A comparison of traditional manufacturing vs additive manufacturing, the best method for the job. *Procedia manufacturing*, *30*, 11-18.
[97]. Peres, R. S., Barata, J., Leitao, P., & Garcia, G. (2019). Multistage quality control using machine learning in the automotive industry. *Ieee Access*, *7*, 79908-79916.
[98]. Petrillo, A., De Felice, F., & Zomparelli, F. (2019). Performance measurement for world-class manufacturing: a model for the Italian automotive industry. *Total Quality Management & Business Excellence*, *30*(7-8), 908-935.
[99]. Rakibul, H., & Samia, A. (2022). Information System-Based Decision Support Tools: A Systematic Review Of Strategic Applications In Service-Oriented Enterprises. *Review of Applied Science and Technology*, *1*(04), 26-65. https://doi.org/10.63125/w3cevz78
[100]. Rathore, H., Jakhar, S. K., Bhattacharya, A., & Madhumitha, E. (2020). Examining the mediating role of innovative capabilities in the interplay between lean processes and sustainable performance. *International Journal of Production Economics*, *219*, 497-508.
[101]. Reinkemeyer, L. (2020). Process mining in action. *Process mining in action principles, use cases and outloook*, *11*(7), 116-128.
[102]. Rejeski, D., Zhao, F., & Huang, Y. (2018). Research needs and recommendations on environmental implications of additive manufacturing. *Additive Manufacturing*, *19*, 21-28.
[103]. Reza, M., Vorobyova, K., & Rauf, M. (2021). The effect of total rewards system on the performance of employees with a moderating effect of psychological empowerment and the mediation of motivation in the leather industry of Bangladesh. *Engineering Letters*, *29*, 1-29.
[104]. Ribeiro, J. P., & Barbosa-Povoa, A. (2018). Supply Chain Resilience: Definitions and quantitative modelling approaches–A literature review. *Computers & industrial engineering*, *115*, 109-122.
[105]. Roy, K., Das, R. N., Ambure, P., & Aher, R. B. (2016). Be aware of error measures. Further studies on validation of predictive QSAR models. *Chemometrics and Intelligent Laboratory Systems*, *152*, 18-33.
[106]. Ruben, R. B., Vinodh, S., & Asokan, P. (2018). Lean Six Sigma with environmental focus: review and framework. *The International Journal of Advanced Manufacturing Technology*, *94*(9), 4023-4037.
[107]. Sabbagh, O., Ab Rahman, M. N., Ismail, W. R., & Wan Hussain, W. M. H. (2017). Methodology implications in automotive product–service systems: a systematic literature review. *Total Quality Management & Business Excellence*, *28*(13-14), 1632-1668.
[108]. Sailor, R. V. (2020). Signal processing techniques. In *Geoid and its geophysical interpretations* (pp. 147-185). CRC Press.
[109]. Salimi, F.-F., & Salimi, F. (2017). *A systems approach to managing the complexities of process industries*. Elsevier.
[110]. Sarkar, S., & Searcy, C. (2016). Zeitgeist or chameleon? A quantitative analysis of CSR definitions. *Journal of cleaner production*, *135*, 1423-1435.
[111]. Sas-Chen, A., Thomas, J. M., Matzov, D., Taoka, M., Nance, K. D., Nir, R., Bryson, K. M., Shachar, R., Liman, G. L., & Burkhart, B. W. (2020). Dynamic RNA acetylation revealed by quantitative cross-evolutionary mapping. *Nature*, *583*(7817), 638-643.
[112]. Sawatzky, R., Porterfield, P., Lee, J., Dixon, D., Lounsbury, K., Pesut, B., Roberts, D., Tayler, C., Voth, J., & Stajduhar, K. (2016). Conceptual foundations of a palliative approach: a knowledge synthesis. *BMC palliative care*, *15*(1), 5.
[113]. Schöggl, J.-P., Baumgartner, R. J., & Hofer, D. (2017). Improving sustainability performance in early phases of product design: A checklist for sustainable product development tested in the automotive industry. *Journal of cleaner production*, *140*, 1602-1617.
[114]. Shalender, K., & Yadav, R. K. (2019). Strategic flexibility, manager personality, and firm performance: The case of Indian Automobile Industry. *Global Journal of Flexible Systems Management*, *20*(1), 77-90.
[115]. Shute, V. J., Sun, C., & Asbell-Clarke, J. (2017). Demystifying computational thinking. *Educational research review*, *22*, 142-158.
[116]. Sireesha, M., Jagadeesh Babu, V., Kranthi Kiran, A. S., & Ramakrishna, S. (2018). A review on carbon nanotubes in biosensor devices and their applications in medicine. *Nanocomposites*, *4*(2), 36-57.

[117]. Spada, S., Ghibaudo, L., Gilotta, S., Gastaldi, L., & Cavatorta, M. P. (2017). Investigation into the applicability of a passive upper-limb exoskeleton in automotive industry. *Procedia manufacturing*, *11*, 1255-1262.
[118]. Syafrudin, M., Alfian, G., Fitriyani, N. L., & Rhee, J. (2018). Performance analysis of IoT-based sensor, big data processing, and machine learning model for real-time monitoring system in automotive manufacturing. *Sensors*, *18*(9), 2946.
[119]. Tagge, E. P., Thirumoorthi, A. S., Lenart, J., Garberoglio, C., & Mitchell, K. W. (2017). Improving operating room efficiency in academic children's hospital using Lean Six Sigma methodology. *Journal of pediatric surgery*, *52*(6), 1040-1044.
[120]. Tao, Y., Huang, M., & Yang, L. (2018). Data-driven optimized layout of battery electric vehicle charging infrastructure. *Energy*, *150*, 735-744.
[121]. Tauro, F., Selker, J., Van De Giesen, N., Abrate, T., Uijlenhoet, R., Porfiri, M., Manfreda, S., Caylor, K., Moramarco, T., & Benveniste, J. (2018). Measurements and observations in the XXI century (MOXXI): Innovation and multi-disciplinarity to sense the hydrological cycle. *Hydrological sciences journal*, *63*(2), 169-196.
[122]. Terwee, C. B., Prinsen, C. A., Chiarotto, A., Westerman, M. J., Patrick, D. L., Alonso, J., Bouter, L. M., De Vet, H. C., & Mokkink, L. B. (2018). COSMIN methodology for evaluating the content validity of patient-reported outcome measures: a Delphi study. *Quality of life research*, *27*(5), 1159-1170.
[123]. Thakkar, J. J. (2020). Structural equation modelling. *Application for Research and Practice*, *285*.
[124]. Thomas, A. J., Francis, M., Fisher, R., & Byard, P. (2016). Implementing Lean Six Sigma to overcome the production challenges in an aerospace company. *Production Planning & Control*, *27*(7-8), 591-603.
[125]. Tobi, H., & Kampen, J. K. (2018). Research design: the methodology for interdisciplinary research framework. *Quality & quantity*, *52*(3), 1209-1225.
[126]. Tran, H. T., Balchanos, M., Domerçant, J. C., & Mavris, D. N. (2017). A framework for the quantitative assessment of performance-based system resilience. *Reliability Engineering & System Safety*, *158*, 73-84.
[127]. Tricco, A. C., Antony, J., Soobiah, C., Kastner, M., MacDonald, H., Cogo, E., Lillie, E., Tran, J., & Straus, S. E. (2016). Knowledge synthesis methods for integrating qualitative and quantitative data: a scoping review reveals poor operationalization of the methodological steps. *Journal of Clinical Epidemiology*, *73*, 29-35.
[128]. Tripathi, S., & De, S. (2019). Data-driven optimizations in IoT: A new frontier of challenges and opportunities. *CSI Transactions on ICT*, *7*(1), 35-43.
[129]. Usuga Cadavid, J. P., Lamouri, S., Grabot, B., Pellerin, R., & Fortin, A. (2020). Machine learning applied in production planning and control: a state-of-the-art in the era of industry 4.0. *Journal of Intelligent Manufacturing*, *31*(6), 1531-1558.
[130]. Valero, E. L. (2019). Advanced Nanomaterials for Inexpensive Gas Microsensors: Synthesis, Integration and Applications.
[131]. Van Der Aalst, W. M., La Rosa, M., & Santoro, F. M. (2016). Business process management: Don't forget to improve the process! *Business & Information Systems Engineering*, *58*(1), 1-6.
[132]. Van Gool, A., Corrales, F., Čolović, M., Krstić, D., Oliver-Martos, B., Martínez-Cáceres, E., Jakasa, I., Gajski, G., Brun, V., & Kyriacou, K. (2020). Analytical techniques for multiplex analysis of protein biomarkers. *Expert review of proteomics*, *17*(4), 257-273.
[133]. Vichard, L., Harel, F., Ravey, A., Venet, P., & Hissel, D. (2020). Degradation prediction of PEM fuel cell based on artificial intelligence. *International Journal of Hydrogen Energy*, *45*(29), 14953-14963.
[134]. Vidal-Ribas, P., Brotman, M. A., Valdivieso, I., Leibenluft, E., & Stringaris, A. (2016). The status of irritability in psychiatry: a conceptual and quantitative review. *Journal of the American Academy of Child & Adolescent Psychiatry*, *55*(7), 556-570.
[135]. Wadhera, T., Kakkar, D., Wadhwa, G., & Raj, B. (2019). Recent advances and progress in development of the field effect transistor biosensor: A review. *Journal of Electronic Materials*, *48*(12), 7635-7646.
[136]. Wang, Y., Liu, S., Afzal, N., Rastegar-Mojarad, M., Wang, L., Shen, F., Kingsbury, P., & Liu, H. (2018). A comparison of word embeddings for the biomedical natural language processing. *Journal of biomedical informatics*, *87*, 12-20.
[137]. Webb, G. I., Hyde, R., Cao, H., Nguyen, H. L., & Petitjean, F. (2016). Characterizing concept drift. *Data Mining and Knowledge Discovery*, *30*(4), 964-994.
[138]. Weichert, D., Link, P., Stoll, A., Rüping, S., Ihlenfeldt, S., & Wrobel, S. (2019). A review of machine learning for the optimization of production processes. *The International Journal of Advanced Manufacturing Technology*, *104*(5), 1889-1902.
[139]. Weimer, D. L., & Vining, A. R. (2017). *Policy analysis: Concepts and practice*. Routledge.
[140]. Wiedemann, G. (2016). *Text mining for qualitative data analysis in the social sciences*. Springer.
[141]. Xu, F., Uszkoreit, H., Du, Y., Fan, W., Zhao, D., & Zhu, J. (2019). Explainable AI: A brief survey on history, research areas, approaches and challenges. CCF international conference on natural language processing and Chinese computing,
[142]. Yan, Z., & Xu, Y. (2018). Data-driven load frequency control for stochastic power systems: A deep reinforcement learning method with continuous action search. *IEEE Transactions on Power Systems*, *34*(2), 1653-1656.
[143]. Yang, J., Dong, J., & Hu, L. (2017). A data-driven optimization-based approach for siting and sizing of electric taxi charging stations. *Transportation Research Part C: Emerging Technologies*, *77*, 462-477.
[144]. Yuste, R., Hawrylycz, M., Aalling, N., Aguilar-Valles, A., Arendt, D., Armañanzas, R., Ascoli, G. A., Bielza, C., Bokharaie, V., & Bergmann, T. B. (2020). A community-based transcriptomics classification and nomenclature of neocortical cell types. *Nature neuroscience*, *23*(12), 1456-1468.

[145]. Zheng, K., Yang, Z., Zhang, K., Chatzimisios, P., Yang, K., & Xiang, W. (2016). Big data-driven optimization for mobile networks toward 5G. *IEEE network*, *30*(1), 44-51.

[146]. Zimmer, K., Fröhling, M., Breun, P., & Schultmann, F. (2017). Assessing social risks of global supply chains: A quantitative analytical approach and its application to supplier selection in the German automotive industry. *Journal of cleaner production*, *149*, 96-109.

[147]. Zobayer, E. (2021a). Data Driven Predictive Maintenance In Petroleum And Power Systems Using Random Forest Regression Model For Reliability Engineering Framework. *Review of Applied Science and Technology*, *6*(1), 108-138. https://doi.org/10.63125/5bjx6963

[148]. Zobayer, E. (2021b). Machine Learning Approaches For Optimization Of Lubricant Performance And Reliability In Complex Mechanical And Manufacturing Systems. *American Journal of Scholarly Research and Innovation*, *1*(01), 61–92. https://doi.org/10.63125/5zvkgg52