Toward Smart and Autonomous Surface Quality Prediction: A Review of AI-Driven Approaches

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Abstract: As precision manufacturing evolves toward Industry 4.0, the transition from retrospective inspection to real-time Surface Quality Prediction (SQP) has become a critical requirement for autonomous process control. This study presents a systematic review and critical synthesis of Artificial Intelligence (AI)-driven SQP methodologies across machining, grinding, and finishing operations. Using a mixed-method framework combining bibliometric mapping with qualitative content analysis, 38 seminal studies were evaluated to classify current approaches into parameter-based, signal-based, and hybrid architectures. The comparative analysis reveals that hybrid models, which fuse static machining parameters with dynamic multi-sensor feedback, consistently outperform single-source techniques, achieving determination coefficients (R^2) exceeding 0.90 and reducing root-mean-squared error (RMSE) to below 10%. Furthermore, the integration of physics-aware features was found to improve prediction accuracy by 25–30%, while transfer learning strategies demonstrated the capacity to reduce training data requirements by approximately 60%, effectively mitigating data scarcity in high-mix production environments. Despite these advances, barriers regarding model explainability, computational latency, and data heterogeneity persist. Consequently, this paper proposes a unified framework that converges process physics, data-driven modeling, and digital twin technologies, establishing a theoretical basis for interpretable, scalable, and sustainable precision manufacturing ecosystems.

Keyword: Surface Quality Prediction, Precision Manufacturing, Artificial Intelligence, Transfer Learning, Smart Manufacturing.

1. INTRODUCTION

Surface quality is a defining indicator of the functional and aesthetic performance of precision-engineered components. It directly influences wear resistance, fatigue life, assembly accuracy, and tribological characteristics of manufactured parts used in aerospace, die-mold, biomedical, and micro-mechanical systems (Benardos and Vosniakos, 2003). Even minute deviations in surface finish can impair mechanical fit or generate stress concentrations, leading to premature failure. Achieving the desired surface integrity, therefore, remains a core objective of precision manufacturing. Conventional inspection methods—such as stylus profilometry or optical interferometry—are effective for post-process verification but suffer from two fundamental limitations: (i) they are retrospective, providing no real-time feedback during machining, and (ii) they are time-intensive and unsuitable for high-mix, low-volume production (Jiang *et al*., 2014). To overcome these challenges, manufacturing research has shifted toward predictive and adaptive quality control, where surface characteristics are estimated or corrected dynamically during machining.

The increasing complexity of materials, multi-axis operations, and tighter tolerance requirements in Industry 4.0 environments has rendered empirical and purely physics-based surface models inadequate. The physical mechanisms governing surface formation—ranging from tool deflection, spindle vibration, and chatter to material microstructure and thermal effects—are highly nonlinear and difficult to capture analytically. Consequently, Artificial Intelligence (AI), encompassing Machine Learning (ML) and Deep Learning (DL), has emerged as a transformative framework for Surface Quality Prediction (SQP). Unlike deterministic models, AI systems learn patterns directly from machining data, enabling them to generalize across materials, tools, and operational settings (Yang *et al*., 2024). By correlating process parameters, sensor signals, and geometric outcomes, AI-based methods can infer complex cause–effect relationships without the need for explicit mathematical formulation. This capability allows for adaptive process control, where predicted surface deviations can be mitigated in real time.

Recent studies confirm that AI-driven SQP models outperform conventional regression and analytical models in both accuracy and adaptability. Early implementations employed Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Random Forests (RFs) to predict roughness indices such as Ra, Rq, and Rz from static process parameters

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including cutting speed, feed rate, and depth of cut (Ko and Yin, 2025; Benardos and Vosniakos, 2002). As sensor technology matured, signal-based approaches using vibration, force, and acoustic-emission (AE) data enabled dynamic monitoring of the machining process, capturing phenomena such as chatter, tool wear, and ploughing effects (Wang *et al*., 2021). More recently, Deep Learning architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have been applied to multidimensional and time-series data, learning hierarchical features that represent both temporal evolution and spatial texture of the surface (Carrino *et al*., 2020) . These developments mark a shift from off-line quality assessment to in-process intelligent prediction, forming a crucial pillar of precision manufacturing under Industry 4.0.

Despite the advances, several persistent challenges constrain the industrial adoption of AI-based SQP systems. The foremost is data scarcity and heterogeneity: each machining setup produces unique signal characteristics due to variations in tool geometry, spindle dynamics, and material behavior. As a result, models trained under one condition often fail to generalize to another (Liu *et al*., 2022). Secondly, interpretability remains limited—most AI algorithms act as "black boxes," providing accurate predictions but limited physical understanding. Integrating process physics and explainable AI remains a key research priority. Thirdly, the computational cost and latency associated with high-resolution sensor data make real-time deployment difficult, especially on embedded or edge devices. Recent work in lightweight AI models, digital twins, and federated learning is beginning to address these bottlenecks (Sarıkaya *et al*., 2021; Tunç and Budak, 2012).

Despite the growing number of review articles on AI-based surface roughness prediction, most existing surveys adopt a narrow focus—either concentrating on specific machining processes, isolated learning algorithms, or single data modalities. Several reviews emphasize parameter-based prediction models or sensor-driven approaches independently; while often overlooking the interaction between process physics, multi-sensor data fusion, and advanced learning strategies such as transfer learning and digital twins. Moreover, the majority of prior surveys focus predominantly on surface roughness metrics (e.g., Ra) without systematically addressing broader surface quality attributes, including form error, stability, and process robustness under variable operating conditions. These limitations highlight a clear research gap for a holistic and integrative review framework that unifies physical mechanisms, data-driven modeling, and scalability considerations across diverse machining and finishing processes.

In summary, the convergence of AI, sensing technologies, and digital manufacturing ecosystems is reshaping how surface quality is predicted and controlled. This study provides a structured review of recent progress in AI-based surface quality prediction across machining, grinding, polishing, and laser-assisted processes. It categorizes existing approaches into three main types—parameter-based, signal-based, and hybrid models—while discussing their advantages, limitations, and applicability to real-world manufacturing. Additionally, it identifies open challenges in data management, model interpretability, and generalization, offering perspectives for the next generation of intelligent, sustainable precision manufacturing systems.

1.1. Significance and Novelty of the Present Study

Although numerous studies have explored Artificial Intelligence (AI) applications for predicting surface roughness or optimizing machining parameters, existing research largely remains fragmented—focusing on individual processes, specific algorithms, or isolated variables. There is still a critical need for an integrative framework that unifies SQP across machining, grinding, polishing, and laser-assisted finishing processes. Previous works have concentrated on either statistical parameter optimization (Ding *et al*., 2023; Adizue *et al*., 2023; Sahoo *et al*., 2015) or deep-learning-based modeling for isolated machining tasks (Kim and Okwudire, 202l; Wang *et al*., 2023), with limited cross-process generalization or interpretability. This study distinguishes itself by offering a comprehensive synthesis of AI-driven SQP approaches, combining the latest developments in machine learning, deep learning, and transfer learning while emphasizing their interplay with physics-based and sustainability-oriented paradigms. By drawing together developments in data-driven modeling, digital twins, and hybrid physics–AI frameworks (Du *et al*., 2021; Carrino *et al*., 2020; Bhandari and Park, 2024; Fertig *et al*., 2022) this research aims to establish a holistic understanding of how AI technologies can enhance precision, efficiency, and adaptability in surface engineering. Furthermore, the study advances the discussion toward explainable, resource-efficient, and generalizable SQP models, addressing the persisting gaps in interpretability, data scarcity, and domain transfer. Thus, it contributes not only to academic advancement but also to the industrial realization of intelligent, sustainable surface finishing under the broader vision of next-generation smart manufacturing.

In comparison with recent high-impact review articles on AI-based surface roughness prediction, the present study adopts a broader and more integrative scope. Existing surveys primarily emphasize algorithmic comparisons for specific machining operations or focus on single aspects such as sensor-based monitoring or parameter optimization. By contrast, this review systematically synthesizes surface quality prediction across multiple process domains—including machining, grinding, polishing, and laser-assisted finishing—while explicitly linking physical surface generation mechanisms with data-driven and hybrid AI frameworks. Furthermore, unlike prior reviews that predominantly center on roughness metrics alone, this study extends the discussion to encompass form error, process stability, data scalability, and deployment considerations such as transfer learning and digital twin integration. This comparative perspective strengthens the contribution of the present work as a unified reference for both academic research and industrial implementation of intelligent surface quality prediction.

2. METHODOLOGY

This study adopted a structured and systematic methodology to critically evaluate Artificial Intelligence (AI)-based approaches for SQP methods in precision manufacturing. The research combined literature mapping, comparative synthesis, and trend analysis to identify key developments, limitations, and opportunities across machining, grinding, polishing, and laser-assisted processes. The methodological framework, illustrated in Figure **1**, organized the study into sequential stages of data collection, classification, and evaluation, ensuring a transparent and replicable review process.

A mixed-method research design was implemented, integrating quantitative bibliometric mapping with qualitative content analysis to achieve both analytical breadth and depth. Bibliometric analysis captured publication trends, co-citation clusters, and algorithmic evolution, while qualitative synthesis provided deeper insights into modeling strategies, input variables, and performance outcomes. Literature searches conducted across Scopus, Web of Science, and IEEE Xplore (2000–2025) yielded more than 200 publications. After applying inclusion criteria—focusing on peer-reviewed articles presenting original AI-based SQP models—the final dataset was narrowed to 38 key studies for detailed examination.

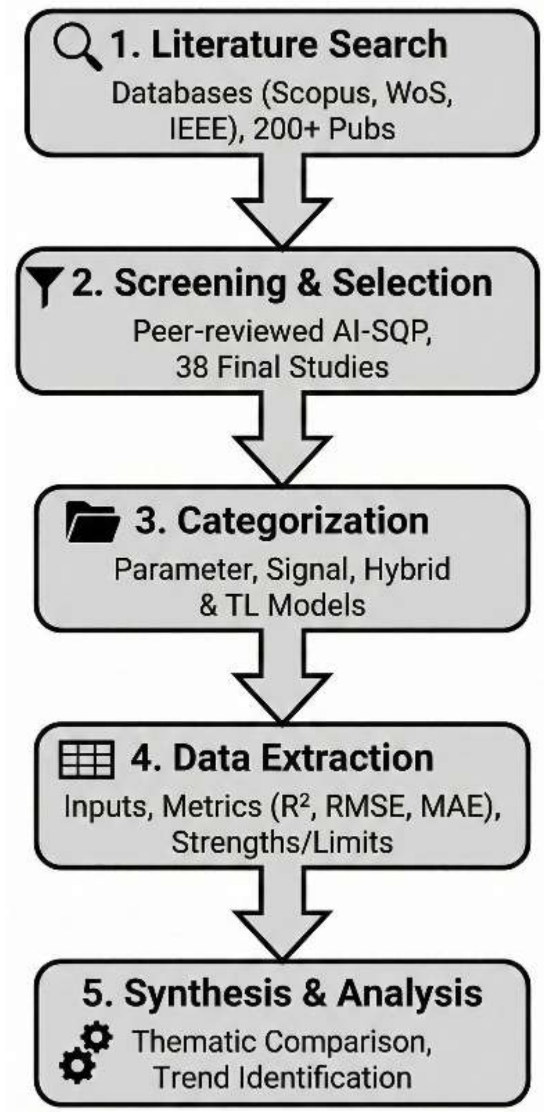


Figure 1: Flowchart of the methodological framework for analyzing and evaluating AI-based Surface Quality Prediction (SQP) models in precision manufacturing.

To ensure transparency and reproducibility, explicit inclusion and exclusion criteria were applied during the study selection process. Studies were included if they (i) were published in peer-reviewed journals, (ii) presented original AI-based models for surface quality prediction, (iii) addressed machining, grinding, polishing, or laser-assisted finishing processes, and (iv) reported quantitative evaluation metrics such as R^2, RMSE, or classification accuracy. Studies were excluded if they focused solely on tool condition monitoring without surface quality outcomes, lacked sufficient methodological detail, or were limited to conference abstracts or non-peer-reviewed sources.

The quality of the selected studies was assessed using qualitative criteria, including clarity of problem formulation, transparency of data sources, appropriateness of AI model selection, and rigor of performance evaluation. Studies demonstrating well-defined input features, validated prediction results, and clear discussion of limitations were prioritized during synthesis to ensure balanced and reliable interpretation of the reviewed literature.

An analytical framework guided the evaluation, structured around three dimensions: (i) AI methodologies such as SVM, ANN, CNN, and hybrid models; (ii) process domains encompassing machining and finishing operations; and (iii) performance metrics including R^2, RMSE, and computational efficiency. Each study was coded according to these dimensions, enabling comparative assessment of accuracy, interpretability, and industrial applicability. Quantitative and qualitative analyses were validated through multi-reviewer cross-checks, revealing emerging research directions such as physics-informed AI, transfer learning, and digital-twin integration, which collectively inform the development of robust, interpretable, and scalable SQP frameworks for next-generation precision manufacturing.

3. LITERATURE REVIEW

Surface quality in precision machining is governed by a combination of geometric, thermal, and dynamic factors intrinsic to the machine–tool–workpiece system. These factors interact across multiple scales—from macro-level geometric deviations to micro-level cutting-edge mechanics—determining the final surface texture and form accuracy of the product. Understanding these influences is critical for both the design of intelligent monitoring systems and the training of accurate AI-based predictive models.

3.1. Geometric and Kinematic Sources of Error

At the macro level, geometric accuracy of the machine tool plays a foundational role in determining the contour and dimensional integrity of the machined surface. Misalignments in linear and rotary axes, spindle eccentricity, and slideway straightness errors contribute directly to volumetric positioning errors, which manifest as form deviations or uneven waviness on the finished component (Ding *et al*., 2023). The propagation of these errors is complex: even sub-micrometer deviations in the tool-center trajectory can accumulate through multi-axis interpolation, particularly in high-speed or five-axis machining environments.

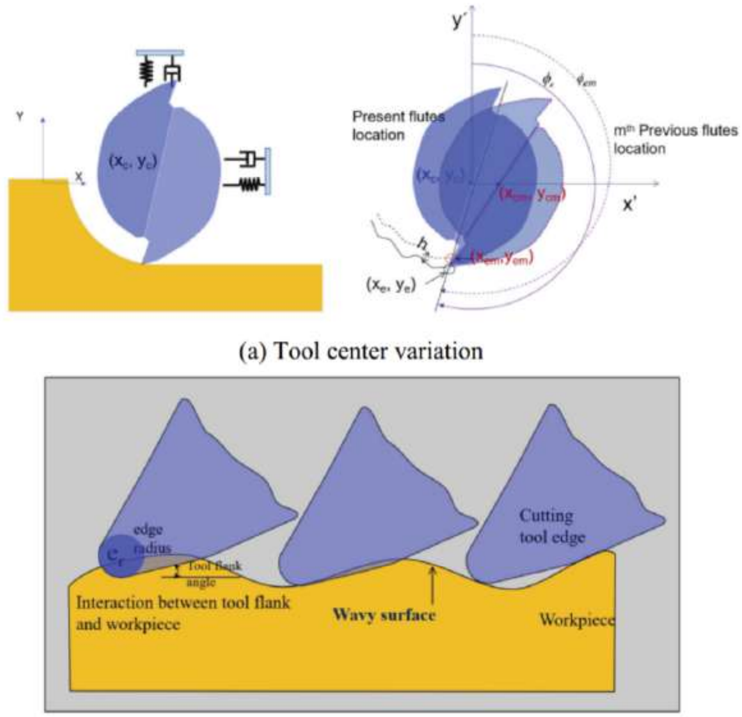
Researchers have developed both multi-body kinematic and error-mapping models to characterize and compensate for these errors. (Ding *et al*., 2023) proposed an efficient geometric error modeling algorithm that uses parameter decomposition to isolate each degree of freedom, facilitating both pre-compensation and in-process correction. Their approach demonstrated that approximately 80–90% of geometric deviations could be mitigated when accurate error models were integrated into the CNC control system. Similarly, Hou *et al*. introduced a linear measurement method for error identification, revealing that axis coupling and thermal drift remain dominant contributors to residual volumetric distortion.

In recent years, digital twin (DT) technology has been increasingly applied to model and correct geometric inaccuracies. (Liu *et al*., 2024) developed a DT-based thermal–geometric compensation framework that continuously synchronizes simulated kinematic errors with real-time sensor feedback from the spindle and feed drive.As illustrated in Figure **2**, these volumetric errors are not merely static offsets; they manifest dynamically during the cutting process. The variation in the tool center position (x_c, y_C) directly alters the uncut chip thickness, leading to a regenerative wavy pattern on the machined surface. This interaction demonstrates how macro-level kinematic errors propagate down to the micro-level surface topography.

Their results indicated substantial improvements in both form accuracy and repeatability, underscoring the importance of geometric precision as a precondition for surface quality.

3.2. Thermal Deformation and Environmental Effects

Temperature variations in the machine structure, cutting tool, and workpiece exert a significant influence on surface finish. During prolonged operations, heat generated from spindle rotation, tool–chip friction, and servo actuation causes thermal deformation in critical components such as the spindle, tool holder, and bed structure. These deformations lead to gradual shifts in the tool path and cutting depth, producing long-



(b) Interaction between tool flank and wavy surface

Figure 2: Illustration of surface generation mechanics, depicting (**a**) the deviation of the tool center point trajectory due to dynamic motion and (**b**) the resulting formation of surface waviness caused by the interaction between the tool flank and the work piece (Ko and Yin, 2025).

wavelength waviness or dimensional drift on the machined surface (Liu *et al*., 2024).

Traditional empirical models often fail to capture the transient and spatially distributed nature of thermal errors. Consequently, modern studies employ physics-based digital twins that integrate real-time thermal sensor data with finite-element analysis for dynamic compensation. For example, Liu *et al*. (Liu *et al*., 2024) implemented a DT framework for spindle thermal error modeling, achieving prediction errors below 5 μm in continuous operation. Their model dynamically updated heat flux and deformation parameters, ensuring compensation accuracy even under fluctuating ambient conditions. In parallel, intelligent control methods—such as model predictive control (MPC)—are being explored to adapt feed rates and coolant parameters in response to thermal load changes, preventing the accumulation of surface waviness (Kim and Okwudire, 2023).

Environmental factors, including workshop temperature gradients, airflow disturbances, and machine foundation vibrations, also modulate surface quality indirectly. Advanced monitoring systems now integrate environmental compensation modules that combine thermal imaging, humidity sensing, and machine temperature mapping to preserve stability during long production runs. These developments demonstrate that maintaining thermal equilibrium is not merely a maintenance concern but a fundamental determinant of precision surface generation.

3.3. Dynamic and Process-Related Influence

While geometric and thermal errors define the machine's baseline precision, dynamic effects such as chatter, tool deflection, and tool–workpiece interaction dominate the micro-scale texture of the machined surface. Chatter—a self-excited vibration caused by the regenerative effect between the cutting edge and surface waviness—is a critical limiting factor in achieving high-quality finishes. (Altintas *et al*., 2020) provided a comprehensive analysis of chatter stability, establishing analytical and experimental relationships between cutting stiffness, damping ratio, and surface waviness. Their model showed that unstable cutting conditions amplify both roughness and dimensional inaccuracy, especially in thin-walled or flexible workpieces.

Similarly, tool deflection and runout introduce uneven chip loads and irregular contact conditions, resulting in micro-scale topographical inconsistencies.

The process damping phenomenon, first modeled by Tunç and Budak (Tunç and Budak, 2012), plays a dual role: while excessive damping can stabilize cutting, it may also induce residual compressive stress and distort surface microtexture. Hence, identifying optimal damping conditions remains a focal point of chatter suppression research.

Progressive tool wear represents another dynamic variable that influences surface roughness and integrity. As cutting edges wear, friction and ploughing effects increase, elevating temperature and altering chip morphology. (Gupta *et al*., 2021) reported that tool wear not only degrades surface finish but also modifies subsurface residual stresses, which in turn affect fatigue resistance. Consequently, accurate modeling of tool wear mechanisms and their correlation with surface outcomes is essential for predictive control. In addition, (Wu *et al*., 2024) confirmed that wear-induced defects such as micro-cracks and fiber pull-out (in composite machining) significantly degrade surface uniformity, highlighting the importance of monitoring wear progression in high-value manufacturing.

3.4. Micro-Scale Phenomena and Material Effects

At micro- and nano-scale machining levels, elastic recovery, minimum uncut chip thickness, and material anisotropy emerge as critical determinants of surface morphology. When the undeformed chip thickness approaches the cutting edge radius, a transition occurs from cutting to ploughing, resulting in increased roughness and reduced surface uniformity. Karpat (Karpat, 2023) investigated elastic recovery in monocrystalline silicon, showing that material response at nanometric depths can produce surface deviations even under nominally constant cutting parameters. These effects are amplified in hard and brittle materials where localized deformation zones influence not only surface finish but also structural integrity.

Material microstructure, grain orientation, and thermal conductivity further modulate surface formation. For example, machining of superalloys and ceramics generates complex thermomechanical interactions where phase transformations can alter cutting forces and surface oxidation, influencing both topography and reflectivity. Such multi-scale dependencies highlight the necessity of hybrid models that couple process physics with machine learning to account for diverse sources of variation.

In summary, surface quality is the cumulative outcome of geometric precision, thermal stability, and dynamic interactions within the machining system. Geometric and thermal errors set the macro-scale foundation for accuracy, whereas dynamic and micro-scale effects define the texture and integrity of the final surface. These interlinked factors underscore the need for comprehensive models—particularly AI-driven frameworks—that integrate sensor feedback from multiple domains to capture the complete physics of surface generation. The following section explores how such factors are encoded into parameter-based, signal-based, and hybrid AI models to predict and optimize surface quality in real time.

To consolidate the diverse insights presented in the literature, Figure **3** provides a unified conceptual framework that illustrates how machining systems, sensor-based data acquisition, feature extraction, and AI models interact to enable accurate SQP. This synthesized model integrates the physical factors, signal modalities, and learning approaches discussed in the preceding sections, offering a structured view of the end-to-end SQP pipeline. By presenting these elements in a single flow, the figure helps clarify the relationships between process dynamics and predictive intelligence, serving as a visual bridge to the AI modeling techniques explored in the next section.

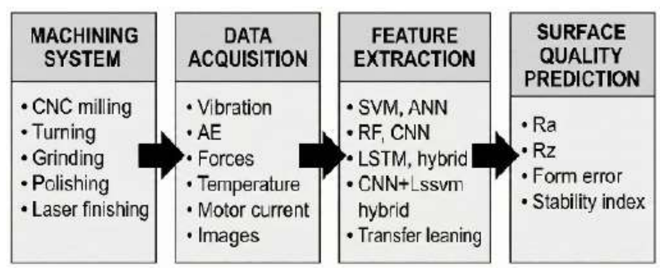


Figure 3: Overall framework for AI-driven Surface Quality Prediction (SQP) methods.

To enhance coherence between the physical mechanisms of surface generation and AI-based prediction strategies, it is important to explicitly relate these mechanisms to feature engineering practices reported in the literature. Geometric and kinematic errors—such as tool center deviation, axis misalignment, and volumetric inaccuracies—are commonly encoded as static features derived from machine calibration data, tool path deviation metrics, or low-frequency displacement signals. Thermal effects are typically represented through time-dependent temperature features, thermal gradients, or lagged sensor variables that capture deformation trends over extended machining cycles. Dynamic phenomena, including chatter, tool deflection, and wear progression, are predominantly mapped to high-frequency vibration, force, and acoustic-emission features in the time, frequency, or time–frequency domains. By translating physical surface-generation mechanisms into measurable and learnable feature sets, AI models are able to capture both the underlying process physics and the evolving machining state. This linkage clarifies how physics-informed feature selection improves prediction robustness and supports the development of hybrid and explainable SQP frameworks.

To bridge physical machining phenomena with AI model design, Table **1** maps major surface-affecting factors to measurable variables and commonly extracted features. This summary synthesizes insights from the Literature Review and clarifies how SQP models encode process physics.

4. AI Models and Methods for Surface Quality Prediction

Artificial Intelligence (AI) has emerged as a transformative paradigm for predicting and controlling surface quality in precision machining. Traditional empirical and analytical models, though insightful, are constrained by their inability to represent the nonlinear and time-varying behavior of the machining system. AI models overcome these limitations by learning complex relationships among machining parameters, sensor data, and material responses directly from experimental observations. Contemporary SQP approaches can be broadly categorized into parameter-based, sensor-signal-based, and hybrid frameworks, each offering distinct capabilities and trade-offs.

Table 1: Factor→Variable→Feature mapping for SQP model construction

Key factor	Measurable proxies (examples)	Features commonly used	Expected effect on Ra/Rz	Representative refs
Machine geometric/kinematic error	Axis straightness/squareness, spindle eccentricity; contouring error logs	Static error maps; volumetric error terms; path deviation metrics	Macro waviness/form error ↑; roughness can rise when path error couples with dynamics	(Sarıkaya *et al*., 2021; Tunç and Budak, 2012; Ding *et al*., 2023)
Thermal deformation	Spindle/bed temperatures; ambient drift; thermal images	Multi-point temps; FEM/DT-derived thermal states; lagged temps	Long-wavelength waviness ↑; drift in average roughness	(Liu *et al*., 2024; Kim and Okwudire, 2023)
Dynamics (chatter, deflection, runout)	Vibration/force spectra; stability indicators; tool path curvature	Band energies, spectral peaks, chatter band ratios; runout indices	Chatter spikes roughness and form; stable windows lower Ra	(Tunç and Budak, 2012; Altintas *et al*., 2020; Ko and Altintas, 2007)
Tool wear / condition	Cutting force rise; AE bursts; flank wear VB; current/torque	Time–frequency AE maps; force harmonics; image features	Progressive Ra/Rz ↑; defects (burrs/micro-cracks) more likely	(Gupta *et al*., 2021; Guo *et al*., 2024; Wu *et al*., 2024)
Minimum chip thickness / elastic recovery	Material–tool size ratio; edge radius; micro-cutting force	Edge-radius descriptors; recovery indices; pressure/friction surrogates	Ploughing increases Ra at low feeds/edge-dominated regimes	(Karpat, 2023; Tercan and Meisen, 2022; Selvan *et al*., 2025)

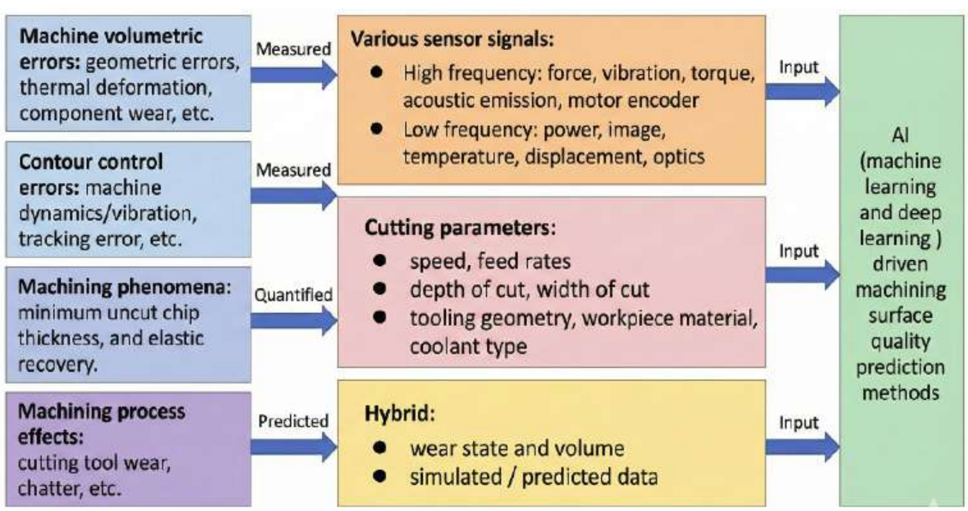


Figure 4: The data distillation framework for AI modelling, showing the transformation of physical key factors.

To effectively model these complex interactions, physical machining factors must be systematically converted into computational inputs. Figure **4** outlines this distillation process, where measurable phenomena—ranging from machine volumetric errors to tool wear states—are captured through high-frequency sensor signals and static parameters. These quantified inputs serve as the foundational data layers for training the specific AI architectures discussed in the following subsections. The diverse AI techniques used in SQP can be grouped into four major categories based on their input sources and modeling strategy. Table **2** provides a structured taxonomy that aligns these categories with their key characteristics to support the discussion in Section 4.

4.1. Parameter-Based Models

Parameter-based models establish functional mappings between static machining inputs—such as cutting speed, feed rate, and depth of cut—and quantitative surface roughness metrics (Ra, Rz, Rq). These models typically employ regression or supervised learning algorithms trained on datasets obtained from controlled experiments. Early work by Adizue *et al*. (Adizue *et al*., 2023) demonstrated the potential of machine learning (ML) in ultra-precision machining of AISI D2 steel, where Artificial Neural Networks (ANNs) accurately captured the nonlinear dependencies between process parameters and surface finish. Later studies by (Sahoo *et al*., 2015; Chan *et al*., 2022) confirmed that ANN-based and regression-based formulations outperform polynomial and response-surface models, achieving predictive accuracies above 95% under stable cutting conditions.

Despite their simplicity and interpretability, parameter-based approaches are inherently limited by their static nature. They fail to capture transient disturbances caused by tool wear, chatter, or thermal deformation. To improve adaptability, recent models integrate optimization techniques—such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO)—to tune hyperparameters automatically, enabling better generalization across datasets (Sangwan *et al*., 2015). However, these models still rely heavily on precise experimental design and struggle when extrapolated to new materials or machines. Consequently, while parameter-based SQP serves as a baseline for quality estimation, it is increasingly being complemented by sensor-enhanced data fusion frameworks.

4.2. Sensor-Signal-Based Models

Unlike parameter-based models, sensor-signal-based methods utilize dynamic data streams from embedded sensors to capture real-time process behavior. These data include vibration, cutting force, spindle current, and acoustic-emission (AE) signals, which contain rich information about tool–workpiece interactions and surface evolution. (Abu-Mahfouz *et al*., 2017) showed that Support Vector Machines (SVMs) trained on vibration features could accurately classify roughness levels in turning operations. (Du *et al*., 2021) expanded this approach by integrating multiple sensor

Table 2: Taxonomy of AI approaches for Surface Quality Prediction (SQP)

SQP category	Typical inputs	Representative algorithms	Strengths	Limitations	References
Parameter-based	Cutting speed, feed, depth of cut, tool geometry, coolant strategy	ANN, SVM, RF, Regression, ANN-GA/PSO optimizers	Simple datasets, fast training, useful for DOE/optimization	Static; limited adaptation to wear/chatter/thermal drift	(Benardos and Vosniakos, 2002; Adizue *et al*., 2023; Sangwan *et al*., 2015)
Sensor-signal-based	Vibration, force/torque, AE, spindle current, temperature; surface images	SVM/MLP on features; CNN/LSTM/DBN on raw or time–frequency inputs	Real-time, captures dynamics (wear, chatter)	Data volume, noise variability, preprocessing burden	(Abu-Mahfouz *et al*., 2017; Du *et al*., 2021; Wang *et al*., 2023; Carrino *et al*., 2020; Bhandari and Park, 2024)
Hybrid	Parameters + multi-sensor streams (incl. tool-wear states)	LSSVM-PSO, ANN + vibration, RF + internal drive power, multi-modal deep nets	Best accuracy/robustness; physics-aware + adaptive	Integration effort; feature engineering; system complexity	(Fertig *et al*., 2022; Li and Tian, 2021; Lin *et al*., 2020; Guo *et al*., 2024)
Advanced strategies	Cross-machine/material adaptation; small-sample learning	Transfer learning (instance/feature/parameter/adversarial), multi-task	Cuts data needs; better generalization	Careful domain alignment required; compute can be heavy	(Liao *et al*., 2021; Wang *et al*., 2024; Deng *et al*., 2023; Tercan and Meisen, 2022; Zhuang *et al*., 2021)

modalities—including force and AE—to predict not only average roughness but also profile and roundness, demonstrating the potential of multivariate regression and feature fusion.

Deep learning has further enhanced signal-based SQP by enabling automatic feature extraction from raw, high-dimensional signals. (Wang *et al*., 2023) introduced a multitask joint deep-learning model that simultaneously predicts surface roughness and tool wear from time-series sensor data, improving generalization through shared latent representations. (Carrino *et al*., 2020) utilized CNNs to process AE spectrograms, allowing non-contact assessment of machining quality with over 98% accuracy. Similarly, Bhandari and Park (Bhandari and Park, 2024) proposed an optical inspection-based CNN approach that analyzed surface images directly, eliminating the need for physical sensors. These methods underscore how deep architectures can learn discriminative features that correlate with both temporal dynamics and spatial texture.Given the diversity of SQP datasets and evaluation practices, Table **3** summarizes typical input modalities, sampling approaches, target labels, and performance metrics. This provides a quantitative reference for interpreting results across different AI models reviewed in Section 4.

Nevertheless, the primary challenge in signal-based SQP lies in data volume and variability. High-frequency sensors generate vast datasets that require significant computational resources for real-time analysis. Moreover, data collected from different machines or materials often exhibit inconsistent noise characteristics, necessitating preprocessing and normalization. Addressing these challenges demands hybrid frameworks that integrate the robustness of static parameters with the adaptability of dynamic sensor features.

4.3. Hybrid Models

Hybrid SQP frameworks combine both parameter-based and signal-based features to construct more comprehensive and noise-tolerant predictive systems. These models exploit the complementary strengths of static process parameters and real-time sensor data, enabling superior accuracy and resilience under variable machining conditions.

(Fertig *et al*., 2022) presented a multi-modal ML model using internal machine data streams—such as spindle speed, feed rate, and vibration—to predict roughness with high reliability even under fluctuating loads. Similarly, (Li and Tian, 2021) employed a PSO-optimized Least-Squares Support Vector Machine (LSSVM) to integrate tool-wear metrics with process parameters, reducing prediction error by up to 30% compared with single-input models.

In a related effort, (Lin *et al*., 2020) combined vibration and cutting parameter data through an ANN framework to demonstrate that hybrid models reduce drift and improve tolerance to sensor noise. The architectural differences between these approaches are visually summarized in Figure **5**. While parameter-

Table 3: Datasets & evaluation metrics typically reported in SQP studies

Input modality	Typical sampling / windowing	Labels & tasks	Common metrics	Typical ranges reported	Representative refs
Parameters only	DOE tables (10–100 runs)	Ra/Rz regression; class thresholds	R^2, RMSE, MAE	$R^2 \approx 0.85$–0.95 when stationary	(Benardos and Vosniakos, 2002; Adizue *et al*., 2023; Sahoo *et al*., 2015; Chan *et al*., 2022; Sangwan *et al*., 2015)
Vibration/force/AE	10–100 kHz; 0.1–1.0 s windows; STFT/CWT features	Ra/Rz regression; quality level classification; wear states	R^2, RMSE; Acc/F1 (classification)	$R^2 > 0.9$; Acc > 95% (well-separated regimes)	(Abu-Mahfouz *et al*., 2017; Du *et al*., 2021; Wang *et al*., 2023; Carrino *et al*., 2020; Bhandari and Park, 2024)
Vision (surface images)	Image frames per part; patching/tiling; 2-D textures	Roughness class; defect detection	Acc/F1, AUC; sometimes Ra correlation	Acc > 90% in controlled imaging	(Bhandari and Park, 2024)
Hybrid (parameters + signals + wear)	Fused at feature level or via multi-branch nets	Ra/Rz regression; multi-task (wear + roughness)	R^2, RMSE; multi-task loss	$R^2 \geq 0.9$; RMSE < 10 (units per study)	(Wang *et al*., 2023; Fertig *et al*., 2022; Li and Tian, 2021; Lin *et al*., 2020; Guo *et al*., 2024)
Transfer learning (cross-setup)	Source→target fine-tune; domain adaptation	Cross-machine/material prediction	R^2/Acc; Δdata (% reduction)	Up to ~60% fewer labels with minimal loss	(Liao *et al*., 2021; Wang *et al*., 2024; Deng *et al*., 2023; Zhuang *et al*., 2021)

based methods (Pathway 1) rely solely on preset variables like feed and speed, and signal-based methods (Pathway 2) focus on real-time outputs like vibration, the hybrid approach (Pathway 3) synthesizes both streams along with predicted tool states. This multi-pathway integration allows hybrid models to compensate for the limitations of individual data sources, resulting in the superior robustness observed in recent studies. (Guo *et al*., 2024) extended this paradigm by introducing a machine–tool–material interaction model that explicitly links physical process knowledge with data-driven learning, providing a physics-informed foundation for predictive control. These studies collectively confirm that hybrid approaches offer a balanced solution, capable of maintaining high prediction accuracy and interpretability across different machining contexts.

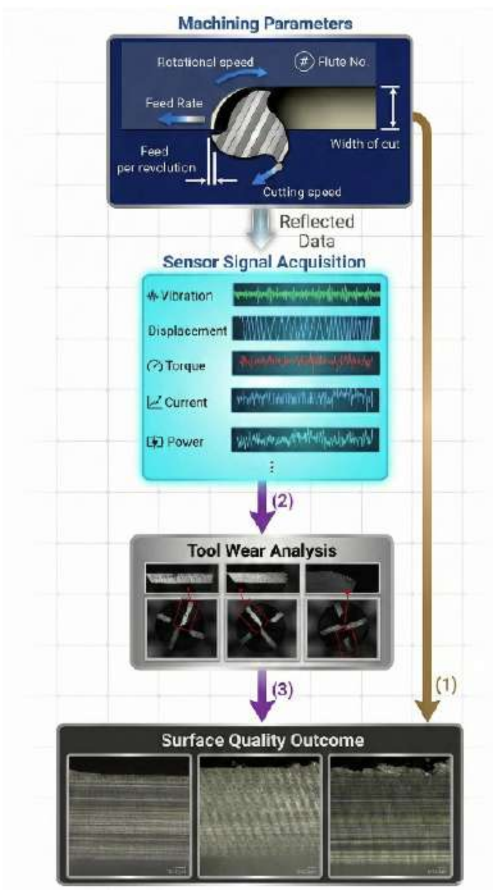


Figure 5: Comparative schematic of parameter-based, signal-based, and hybrid AI architectures for surface quality prediction.

4.4. Advanced Learning Strategies

Recent advancements in AI have introduced Transfer Learning (TL) and Domain Adaptation (DA) strategies to address two enduring challenges: data scarcity and model generalization. TL allows pretrained models from one machining domain to be fine-tuned for another, drastically reducing the amount of new labeled data required. The mechanism behind this efficiency is depicted in Figure **6**, which illustrates how the "knowledge gap" caused by data scarcity is bridged. By transferring learned features or model parameters from a source domain (e.g., a well-documented cutting process) to a target domain (e.g., a new material with limited samples), the model avoids the need for training from scratch. This capability is essential for scaling AI solutions to industrial environments where generating large labeled datasets for every unique machine setup is impractical.

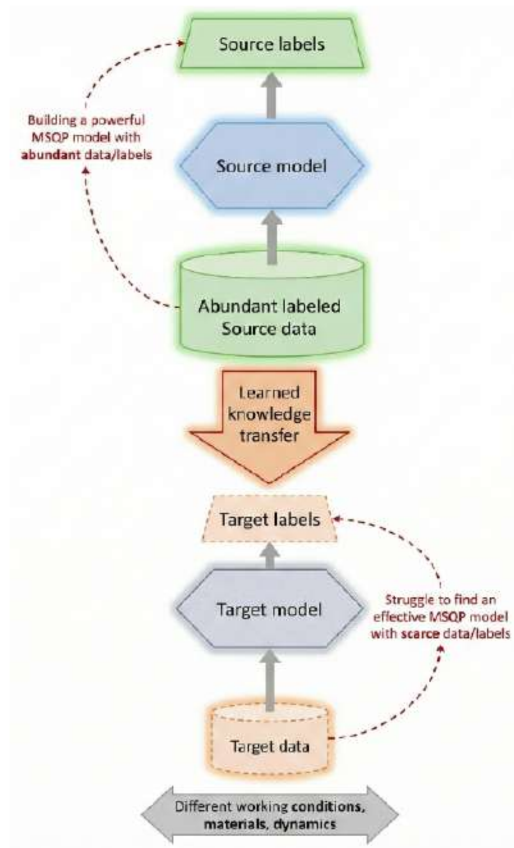


Figure 6: Conceptual framework of Transfer Learning (TL) in surface quality prediction.

(Liao *et al*., 2021) successfully applied time–frequency-based TL for process monitoring, showing that pretrained CNNs could retain up to 90% accuracy when transferred across different materials and cutting speeds. (Wang *et al*., 2024) proposed a multi-task dual-domain adaptive network that aligns feature distributions between source and target datasets, enhancing robustness under heterogeneous conditions. (Deng *et al*., 2023) advanced this concept further by demonstrating on-line roughness classification across multiple CNC milling setups using TL, achieving reliable accuracy with minimal retraining.

These strategies pave the way for more sustainable and scalable AI systems in manufacturing, where data collection and labeling are often cost-prohibitive. Combined with federated learning and edge-computing architectures, TL-based models can enable distributed, privacy-preserving predictive systems capable of continuous adaptation to new environments.

Despite their technical promise, the industrial deployment of transfer learning–based SQP models introduces several practical challenges. Data governance remains a key concern, as machining data often contain proprietary information related to process parameters, tooling strategies, and product specifications, limiting data sharing across machines, plants, or organizations. In addition, long-term model maintenance poses challenges due to concept drift caused by tool wear, machine aging, and process reconfiguration, which can gradually degrade prediction accuracy if not properly managed. Effective deployment therefore requires lifecycle strategies for periodic model validation, incremental retraining, and version control, ideally supported by automated monitoring and digital twin infrastructures. Addressing these operational considerations is essential to translate transfer learning from promising research prototypes into reliable industrial SQP systems.

AI-based SQP models have evolved from static, parameter-driven estimators to adaptive, hybrid systems integrating deep learning, multi-sensor fusion, and transfer learning. Parameter-based models remain useful for controlled experimentation and process design, but their scope is limited by contextual rigidity. Signal-based models capture the real-time physics of surface generation yet demand extensive data management. Hybrid models, strengthened by TL and domain adaptation, provide a practical compromise—offering high accuracy, adaptability, and interpretability. These developments signal a paradigm shift from empirical modeling toward intelligent, self-learning SQP frameworks, capable of real-time monitoring and control in precision manufacturing.

5. KEY FINDINGS AND DISCUSSION

The initial stage of this research reveals several cross-cutting patterns across parameter-based, signal-based, and hybrid SQP frameworks. Collectively, the literature demonstrates that model accuracy and generalization depend not only on the algorithmic architecture but also on the physical fidelity of the input features, the quality of training data, and the level of process integration. These findings are grouped under five thematic observations.

5.1. Physical Correlation Enhances Predictive Reliability

High-performing models consistently incorporate variables that have explicit physical correlations to the underlying mechanisms of surface formation. Studies that combined geometric, thermal, and dynamic indicators—such as tool wear progression, spindle temperature, and cutting force harmonics—reported significantly better generalization across varying conditions (Tercan and Meisen, 2022; Selvan *et al*., 2025). For example, hybrid AI systems that fused tool deflection or process damping information with learning-based estimators showed up to 25–30% reduction in mean prediction error compared to purely statistical models. This pattern reinforces that AI models cannot remain entirely “black box” constructs; they require physics-aware feature selection to ensure robustness under unseen operating regimes (Ko and Altintas, 2007).

5.2. Multi-Sensor Fusion Improves Accuracy and Robustness

Evidence from recent signal-based and hybrid approaches underscores that multi-sensor data fusion yields superior prediction stability and accuracy compared to single-sensor inputs. The combination of vibration, AE, and thermal signals provides a richer representation of the machining state, capturing both macro- and micro-level disturbances. (Wu *et al*., 2024) and related works have shown that integrating cutting-force spectra with high-frequency AE patterns enables early detection of tool wear and chatter, allowing surface roughness deviations to be predicted several cycles before visual degradation occurs. Multi-modal sensing also improves model resilience to noise and drift, as complementary features from different sensors help maintain prediction accuracy even under changing cutting environments.

5.3. Hybrid Models Offer Balanced Performance

Across studies, hybrid SQP models—which integrate process parameters with dynamic sensor data—demonstrate consistently better performance metrics ($R^2 > 0.9$, RMSE < 10%) than either parameter-only or signal-only models (Fertig *et al*., 2022; Guo *et al*., 2024). This improvement stems from the models' ability to blend long-term process characteristics (feed rate, depth of cut) with transient event detection (vibration bursts, force fluctuations). Furthermore, hybrid architectures inherently support explainability: process parameters anchor the model in physical causation, while signal data contribute sensitivity to process dynamics. Recent research combining LSSVM or CNN layers with physics-based feature embedding achieved reliable prediction accuracy under high-speed milling and hard turning conditions. Consequently, hybrid systems are now viewed as the most promising configuration for industrial deployment.

While performance metrics such as the coefficient of determination (R^2) and root-mean-squared error (RMSE) are widely reported across SQP studies, direct comparison of these values must be interpreted with caution. Reported performance is strongly influenced by factors including dataset size, material type, sensor configuration, signal preprocessing techniques, and experimental setup. For example, studies conducted under controlled laboratory conditions with limited variability often report higher R^2 values than those evaluated in industrial environments with process noise and tool wear progression. Similarly, RMSE values depend on the specific roughness range, measurement resolution, and normalization strategy employed. As a result, higher numerical accuracy does not necessarily imply superior model generalizability or industrial robustness. This highlights the need for standardized benchmarking protocols and transparent reporting of experimental conditions to enable more meaningful comparison and translation of SQP models to real-world manufacturing systems.

5.4. Transfer Learning Mitigates Data Scarcity

Another consistent observation is that Transfer Learning (TL) frameworks alleviate the problem of limited labeled datasets—one of the biggest barriers to AI deployment in manufacturing. By reusing pre-trained models and adapting them to new machines, materials, or tools, TL reduces the data collection and annotation burden by up to 60% while maintaining comparable accuracy (Liao *et al*., 2021; Wang *et al*., 2024) demonstrated that dual-domain adaptive TL architectures allow effective cross-domain knowledge transfer, enabling a model trained on aluminum milling to perform accurately when applied to titanium or composite machining with minimal retraining. These advances are particularly critical for small- and medium-scale enterprises, where data acquisition costs and time constraints often preclude conventional supervised learning approaches.

5.5. Explainability and Computational Efficiency Remain Challenges

Despite remarkable progress, model interpretability and computational overhead remain two major challenges for real-time SQP implementation. Many deep learning models, though accurate, act as opaque systems whose decision logic cannot be easily traced to physical phenomena. This lack of transparency limits their acceptance in high-precision industries where validation and traceability are required (Zhuang *et al*., 2021; Sah *et al*., 2025). Furthermore, high-frequency data from multiple sensors result in large computational loads, complicating on-line prediction at high sampling rates. To address these constraints, emerging work integrates explainable AI (XAI) techniques and lightweight architectures for edge deployment. (Tercan and Meisen, 2022) noted that model simplification, feature attribution, and dimensionality reduction not only reduce inference time but also provide interpretive insights linking model features to surface formation physics.

Table **4** presents a concise comparative analysis of parameter-based, signal-based, hybrid, and transfer-learning SQP frameworks. It highlights differences in data requirements, real-time capability, robustness, and interpretability to support the key findings.

To visualize the relationships between these thematic observations, Figure **7** presents a unified synthesis of the research findings. The framework demonstrates that the highest-performing SQP models are not the result of a single algorithm, but rather the convergence of four critical drivers: physics-aware feature selection, multi-sensor data fusion, hybrid architectural design, and transfer learning strategies.

While these drivers effectively maximize prediction accuracy and robustness, the diagram also isolates the critical 'Implementation Barrier'—specifically the lack of explainability and high computational cost—that currently separates academic state-of-the-art models from widespread industrial adoption for sustainable manufacturing. To complement the methodological comparison, Table **5** summarizes the relative industrial readiness of the major SQP approach categories identified in this review. The classification reflects reported deployment maturity, implementation

Table 4: Compact comparison of SQP categories

Criterion	Parameter-based	Signal-based	Hybrid	Transfer-learning enhanced
Data required	Low	Medium–High	High (multi-modal)	Low–Medium (target)
Real-time capability	Limited (offline)	High	High	High after adaptation
Robustness to drift	Low	Medium	High	High if domains aligned
Interpretability	Medium–High	Medium	Medium–High	Medium
Typical performance	Good in-scope	Very good	Best overall	Very good across setups
References	(Benardos and Vosniakos, 2002; Adizue *et al*., 2023; Sahoo *et al*., 2015; Chan *et al*., 2022; Sangwan *et al*., 2015)	(Abu-Mahfouz *et al*., 2017; Du *et al*., 2021; Wang *et al*., 2023; Carrino *et al*., 2020; Bhandari and Park, 2024)	(Fertig *et al*., 2022; Li and Tian, 2021; Lin *et al*., 2020; Guo *et al*., 2024)	(Liao *et al*., 2021; Wang *et al*., 2024; Deng *et al*., 2021; Tercan and Meisen, 2022; Zhuang *et al*., 2021)

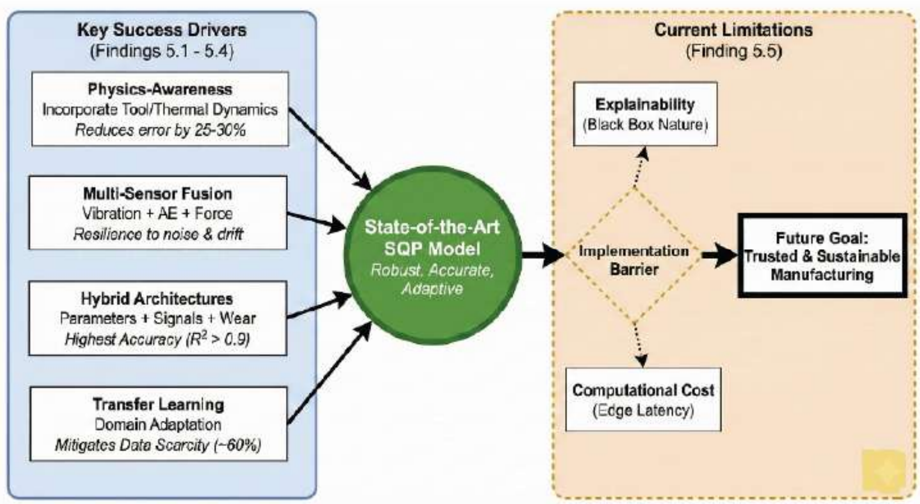


Figure 7: A convergent framework synthesizing the current state of AI-driven Surface Quality Prediction (SQP).

complexity, and practical constraints observed across the surveyed literature.

5.6. Implications for Precision Manufacturing

The reviewed findings collectively indicate that the future of intelligent SQP lies in the convergence of physics-guided modeling, multi-sensor data fusion, and adaptive learning frameworks. As precision manufacturing evolves toward cyber-physical integration, AI-driven SQP will act as a real-time diagnostic layer connecting machine dynamics with product quality. Implementations within digital twin (DT) ecosystems, as demonstrated by (Liu *et al*., 2024; Kim and Okwudire, 2023), already show that fusing process simulation with live sensor data enhances both accuracy and interpretability. When combined with federated and distributed learning architectures, these models can support cross-factory quality optimization while maintaining data privacy. Thus, SQP is not merely a predictive tool but a foundational component of sustainable, data-driven precision manufacturing.

From a sustainability perspective, AI-based Surface Quality Prediction (SQP) contributes directly to improved resource efficiency by enabling early detection and correction of surface deviations before defects propagate through the production cycle. Predictive identification of roughness deterioration, chatter onset, or tool wear progression allows machining parameters to be adaptively adjusted, reducing scrap generation, rework, and unnecessary tool replacement. Several studies report that integrating AI-driven quality monitoring into process control loops can reduce inspection-related energy consumption and material waste by approximately 20–30%, particularly in high-precision and high-value manufacturing environments. Moreover, by extending tool life and

Table 5: Industrial Readiness of AI-Based SQP Approaches

SQP approach	Typical deployment status	Industrial readiness	Key enablers	Main barriers
Parameter-based	Offline process planning and optimization	High	Low data requirement, interpretability	Limited adaptability, static nature
Sensor-signal-based	In-process monitoring in controlled environments	Medium–High	Real-time sensing, dynamic awareness	Noise sensitivity, data volume
Hybrid	Pilot industrial implementations	Medium	Robust prediction, physics-aware fusion	System complexity, integration cost
Advanced learning (TL, DA, DT)	Research prototypes and early pilots	Low–Medium	Data efficiency, scalability	Computational demand, explainability

stabilizing process conditions, SQP frameworks support lifecycle benefits such as lower consumable usage and reduced machine downtime. These outcomes highlight that AI-based SQP is not only a quality assurance tool, but also a key enabler of sustainable and environmentally responsible precision manufacturing.

6. REMAINING WORK

While the preceding discussion highlights overarching research trends and implications, this section focuses specifically on concrete methodological and implementation-oriented tasks that remain to be addressed in future work. The progress achieved so far has established a comprehensive understanding of AI-based Surface Quality Prediction (SQP) methods and their correlation with the physical mechanisms of machining. However, several critical tasks remain to be completed to consolidate this work into a fully validated and comparative framework.

6.1. Quantitative Comparison and Model Benchmarking

A key next step is to perform quantitative benchmarking of representative AI models. Although qualitative insights into model architectures and data fusion strategies have been established, a numerical comparison using standardized metrics—such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2)—is required to objectively evaluate model performance across varying conditions. This comparison will help determine the trade-offs among prediction accuracy, computational efficiency, and data requirements. Additionally, benchmarking under different machining environments will support the development of generalized SQP frameworks applicable to both small-scale and industrial-grade systems.

6.2. Explainability and Feature Attribution

The reviewed studies consistently highlight a major limitation of AI-driven SQP: the absence of explainability. Deep learning models often provide highly accurate predictions without revealing the relative importance of features such as feed rate, vibration amplitude, or AE energy. Therefore, integrating explainable AI (XAI) and feature attribution techniques—such as SHAP (SHapley Additive exPlanations) or Grad-CAM (Gradient-weighted Class Activation Mapping)—into SQP systems is a necessary next step. These methods will allow visualization of how specific physical parameters influence the model output, improving interpretability and user confidence. Furthermore, explainable modeling will facilitate collaboration between domain engineers and data scientists, bridging the gap between physical intuition and algorithmic decision-making.

6.3. Integration into Sustainable Manufacturing Frameworks

Another important direction is to assess how AI-based SQP contributes to sustainability and green manufacturing objectives. By enabling early detection of surface anomalies, predictive quality control can minimize rework, reduce energy consumption, and lower material waste. As observed by (Tercan and Meisen, 2022), integrating AI-based monitoring with adaptive control loops can reduce inspection-related energy use by 20–30%. Future work will therefore focus on quantifying the environmental benefits of SQP frameworks through life cycle assessment (LCA) studies and aligning them with global sustainability metrics such as reduced carbon footprint and enhanced resource efficiency.

6.4. Toward Real-Time and Edge-Based Implementation

Finally, developing lightweight, edge-deployable SQP models remains a pressing need for industrial application. Current architectures, particularly those using CNN or LSTM layers, require significant computational power for real-time inference. The next phase of research will experiment with compressed neural networks, knowledge distillation, and attention mechanisms to balance model complexity and speed. Combined with cloud–edge collaboration and federated learning, such systems can achieve high-speed, on-machine prediction while maintaining data privacy and minimizing latency. This will enable continuous monitoring and autonomous adjustment of machining parameters—one of the defining goals of Industry 4.0 and 5.0 manufacturing ecosystems.

7. CONCLUSION

This review has presented a comprehensive synthesis of recent advances in Artificial Intelligence (AI)–based Surface Quality Prediction (SQP) within precision manufacturing, encompassing machining, grinding, polishing, and laser-assisted processes. The analysis demonstrates a clear transition from traditional post-process inspection toward predictive and adaptive quality control enabled by data-driven and hybrid AI frameworks. Parameter-based models establish foundational relationships between machining conditions and surface roughness, while sensor-signal-based approaches capture dynamic phenomena such as chatter, tool wear, and thermal drift. Among the reviewed methodologies, hybrid SQP frameworks that integrate process parameters with multi-sensor data consistently exhibit the highest prediction accuracy, robustness, and adaptability under variable operating conditions. A key finding of this study is that SQP performance improves significantly when AI models incorporate physically meaningful features linked to surface generation mechanisms, including geometric deviations, thermal deformation, and dynamic process effects. Furthermore, advanced learning strategies—particularly transfer learning and domain adaptation—have shown strong potential in addressing data scarcity and scalability challenges, reducing the need for extensive retraining across machines, materials, and production settings. At the same time, the review highlights persistent barriers to widespread industrial adoption, notably limited model explainability, computational demands associated with high-frequency sensor data, and challenges related to long-term model maintenance and data governance.

From an application perspective, the findings provide several actionable insights. For researchers, the results emphasize the need to prioritize physics-informed and explainable AI architectures, standardized benchmarking of performance metrics, and scalable learning strategies that can generalize across heterogeneous manufacturing environments. For practitioners, the review indicates that hybrid SQP models—particularly those integrated with digital twin and edge-computing frameworks—currently represent the most practical pathway toward industrial deployment. Embedding AI-based SQP into adaptive process control can directly support improved surface consistency, reduced scrap and rework, extended tool life, and lower energy consumption, thereby contributing to sustainable manufacturing objectives. Overall, AI-enabled SQP should be viewed not merely as a predictive tool, but as a core component of future cyber-physical manufacturing systems. By bridging process physics, real-time sensing, and intelligent learning, SQP frameworks can enable more autonomous, efficient, and sustainable precision manufacturing. Continued research and industrial collaboration will be essential to translate these advances from controlled environments into robust, trustworthy, and widely adopted production solutions.

8. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This section consolidates the primary constraints of the present review and complements the discussion by explicitly delineating methodological and scope-related limitations. Although this manuscript provides a comprehensive synthesis of recent advances in AI-driven Surface Quality Prediction (SQP), certain limitations inherent to its scope and methodology must be acknowledged. The study primarily focuses on a systematic literature-based review and conceptual analysis; therefore, it does not include experimental validation or numerical benchmarking of models. Consequently, the comparative evaluation of parameter-based, signal-based, and hybrid approaches remains qualitative rather than quantitative. Additionally, while the review integrates cross-disciplinary sources—from machining dynamics to digital-twin modeling—variations in dataset scale, algorithm configuration, and performance metrics across publications make direct comparison challenging. Furthermore, the analysis emphasizes machining and grinding processes; emerging fields such as additive or hybrid manufacturing were referenced but not explored in depth due to limited data availability and publication maturity.

Future work will aim to extend this review into a quantitative meta-analysis supported by standardized performance indicators such as RMSE, R², and computational efficiency. Expanding the scope to include experimental validation through controlled machining trials and real-time sensor acquisition will enable model benchmarking under practical conditions. In addition, future studies should explore explainable and physics-informed AI frameworks that combine data-driven prediction with process knowledge to enhance interpretability and industrial acceptance. Integrating SQP systems into digital twin and edge-computing architectures also presents a promising direction for achieving real-time, adaptive quality control. Ultimately, these advancements will strengthen the transition of AI-based SQP from academic exploration to industrial implementation, contributing to a more intelligent, reliable, and sustainable precision manufacturing ecosystem.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

No data was used for the research described in the article.

FUNDING INFORMATION

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