

Review

Intelligent Vibration Monitoring and Chatter Control in Sustainable Machining: From Physics-Based Models to Machine Learning and Digital Twins

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ABSTRACT: Chatter is a persistent self-excited vibration problem in machining that affects productivity, surface quality, tool life, energy consumption, and process sustainability. This review examines the evolution of intelligent chatter management and evaluates its implications for sustainable machining. The review considers the transition from analytical stability prediction and stability-lobe methods to sensor-based monitoring, machine learning, physics-informed approaches, adaptive control, and digital twins, with particular attention to deployment readiness and sustainability evidence. The literature indicates that productivity and surface-quality effects of chatter are well established, whereas direct evidence concerning energy use, material waste, carbon emissions, life-cycle impacts, and component durability remains comparatively limited. Data-driven approaches offer strong potential for real-time monitoring but face challenges related to transferability, changing process conditions, and validation across different machines, tools, materials, and geometries. A clear gap is identified between technology maturity and sustainability-evidence maturity. To address this gap, the review introduces the Sustainability Evidence Level (SEL) framework for organizing and assessing sustainability evidence according to whether reported benefits are measured, modelled, or scenario-assumed. The review highlights the need for future studies to integrate intelligent chatter management with measurable resource-use, productivity, durability, and environmental indicators.

Keywords: Chatter; Sustainable machining; Digital twin; Machine learning; Physics-informed models; Condition monitoring

1. Introduction

1.1. Machining Chatter as a Manufacturing Problem

Chatter is a self-excited vibration sustained by the cutting process. It arises when the interaction between cutting forces and machine–tool–workpiece dynamics becomes unstable, impairing surface quality, dimensional

accuracy, tool life, and productivity [1–5]. In regenerative chatter, waviness left by a previous cutting pass modifies the chip thickness encountered during the next pass, creating a delayed feedback mechanism.

Stability prediction identifies operating conditions that avoid this instability. However, changes in tool wear, workpiece geometry, fixturing, and cutting conditions can shift the stability boundary during production, particularly in flexible and thin-walled components [6]. These changes motivate in-process monitoring and adaptive intervention [7].

1.2. Why Chatter Should Also Be Treated as a Sustainability Problem

Chatter has sustainability implications because its manufacturing consequences can increase the resources required to produce an acceptable component. Energy-related studies examine machine-tool electrical demand and chatter-free parameter optimization [8,9], while tool-life investigations address the resource consequences of unstable cutting [10]. Other studies connect stability with carbon-oriented optimization and trade-offs among cutting energy, wear, and surface finish [11,12]. Surface damage may also affect component durability after manufacture [13]. Digital-twin frameworks increasingly incorporate energy, productivity, or environmental objectives into stability management [14,15].

These links require different evidence: vibration and roughness characterize process behavior, whereas energy per part, tool consumption, discarded material, and life-cycle impacts quantify downstream outcomes. Improved chatter control should therefore not be interpreted automatically as demonstrated sustainability improvement.

The review examines these pathways in Section 3 and distinguishes measured, modelled, and assumed benefits through the Sustainability Evidence Level (SEL) framework in Section 2.6.

1.3. Evolution Toward Intelligent Chatter Management

Chatter management now combines offline stability prediction with online sensing, machine learning (ML), and adaptive control. Sensor signals reveal the actual process state, while learning methods classify instability or estimate stability boundaries under variable operating conditions. Transfer learning and noise-resistant representations address the difficulty of applying models beyond their original training conditions [16,17].

Physics-informed and hybrid approaches incorporate machining dynamics into learning, including Bayesian updating of uncertain structural, cutting-force, and process-damping parameters [18,19]. Digital twins extend this integration by updating a virtual process representation from measurements and supporting corrective decisions [20,21]. These approaches have complementary roles: physical models explain instability, data support adaptation, and control translates predictions into intervention. Their deployment requirements are examined in Sections 4–8.

1.4. Limitations of Existing Reviews

Existing reviews cover the main components of chatter management. General and stability-focused reviews examine mechanisms, prediction, and avoidance [2,22]. Complementing these reviews, individual studies have incorporated chatter-stability information into surface-roughness prediction, linking dynamic behavior with manufacturing quality [23]. Monitoring reviews address sensing, signal processing, and intelligent classification [7,24–26]; suppression reviews compare passive and active interventions [27]; and micro-milling reviews integrate cutting mechanics, stability, monitoring, and suppression within a process-specific perspective [28]. Digital-twin reviews further cover machine-tool modelling, identification, optimization, and control [29].

Sustainable-machining reviews examine energy use, carbon emissions, lubrication, resource efficiency, and digital technologies across broader manufacturing contexts [30,31]. However, the sustainability implications of chatter-specific prediction, monitoring, and control have received comparatively limited

integrated attention. The present review connects these perspectives by examining the sustainability evidence associated specifically with chatter prediction, monitoring, and control. Its focus is the relationship between reported technical performance and quantified resource or environmental outcomes.

1.5. Objectives and Contributions

This review examines intelligent chatter management through its physical mechanisms, technological approaches, and sustainability consequences. It makes four contributions: a causal framework connecting chatter to manufacturing and resource losses; a synthesis of prediction, monitoring, learning, and control methods; a SEL classification of reported outcomes; and an assessment of evidence gaps and priorities for industrial validation. The five research questions in Section 2.1 organize this analysis. The review distinguishes among technological capability, deployment readiness, and evidence of sustainability rather than treating them as equivalent measures of progress.

2. Review Methodology

2.1. Review Design and Research Questions

This study was designed as a structured critical review with evidence synthesis without meta-analysis. It integrates research on machining chatter mechanisms, prediction, monitoring, suppression, intelligent control, and sustainability-related manufacturing outcomes. The review does not claim to be exhaustive or to fully comply with the PRISMA 2020 reporting framework [32], as the original database retrieval and screening histories were not retained. Instead, it provides a transparently defined thematic search strategy, explicit eligibility criteria, and a curated study-level evidence corpus. The synthesis draws on the principles of Synthesis Without Meta-analysis (SWiM) [33] to organize and interpret heterogeneous technical and sustainability findings.

Five research questions guide the review, each addressing a distinct analytical dimension:

RQ1—Causal pathways: Through which physical, manufacturing, resource, and life-cycle pathways does machining chatter generate losses in energy efficiency, tool life, material utilization, product quality, productivity, and component performance?

RQ2—Technological evolution: How has chatter management evolved from physics-based stability prediction and conventional signal-processing approaches toward machine learning, physics-informed and hybrid intelligence, digital twins, and adaptive or autonomous control?

RQ3—Deployment readiness: To what extent do sensing and intelligent chatter-management approaches demonstrate generalization across operating conditions, robustness to noise and process variability, interpretability, and the real-time capability required for practical intervention?

RQ4—Sustainability evidence: What level of measured, modelled, or otherwise explicitly quantified sustainability evidence has been demonstrated for chatter prediction, avoidance, detection, and suppression strategies, particularly with respect to energy consumption, tool consumption, machining time, material waste, rework, scrap, component life, carbon emissions, and life-cycle impacts?

RQ5—Evidence and research gaps: Which methodological, technological, and validation gaps currently prevent intelligent chatter management from progressing beyond conventional performance proxies toward direct sustainability assessment and optimization?

2.2. Information Sources and Search Strategy

A structured literature search strategy was developed using the Web of Science Core Collection and Scopus to identify studies addressing machining chatter, intelligent monitoring and control, and associated manufacturing and sustainability outcomes. Two complementary search streams were established. Stream A focused on intelligent chatter prediction, monitoring, detection, and control, including sensor-based methods, machine learning, deep learning, physics-informed approaches, digital twins, and reinforcement

learning. Stream B addressed chatter-related manufacturing and sustainability consequences, including energy consumption, tool wear and life, surface integrity, productivity, material waste, component durability, and environmental impacts.

The database searches were conducted on 9 October 2026 using the Topic field (TS) in Web of Science and the Title–Abstract–Keywords field (TITLE-ABS-KEY) in Scopus. The intended search restrictions covered English-language journal articles and conference papers published between 2010 and 2026. The Boolean expressions used to define the two search streams are presented below.

Stream A—Intelligent chatter monitoring and control

Web of Science:

TS = ((chatter OR “regenerative vibration”) AND (machining OR milling OR turning OR boring) AND (monitor* OR detect* OR predict* OR suppress* OR control*) AND (sensor* OR “machine learning” OR “deep learning” OR “physics-informed” OR “digital twin” OR “reinforcement learning”))

Scopus:

TITLE-ABS-KEY ((chatter OR “regenerative vibration”) AND (machining OR milling OR turning OR boring) AND (monitor* OR detect* OR predict* OR suppress* OR control*) AND (sensor* OR “machine learning” OR “deep learning” OR “physics-informed” OR “digital twin” OR “reinforcement learning”))

Stream B—Chatter and sustainability consequences

Web of Science:

TS = ((chatter OR “machining vibration” OR “process instability”) AND (machining OR milling OR turning OR boring) AND (energy OR power OR “specific energy” OR “tool wear” OR “tool life” OR “surface integrity” OR “surface quality” OR scrap OR rework OR waste OR productivity OR “material removal rate” OR fatigue OR “service life” OR carbon OR emission*))

Scopus:

TITLE-ABS-KEY ((chatter OR “machining vibration” OR “process instability”) AND (machining OR milling OR turning OR boring) AND (energy OR power OR “specific energy” OR “tool wear” OR “tool life” OR “surface integrity” OR “surface quality” OR scrap OR rework OR waste OR productivity OR “material removal rate” OR fatigue OR “service life” OR carbon OR emission*))

The database retrieval results are summarized in Table 1. Before filtering, the searches returned 4470 records across the four database-specific streams, including records appearing in multiple streams. After filtering, 4074 search hits remained. Combining Streams A and B using the Boolean OR operator yielded 976 distinct records within Web of Science and 2304 within Scopus, corresponding to 3280 database records before cross-database deduplication.

Table 1. Database-specific literature-search results for intelligent chatter management and sustainability-related machining studies.

Database	Search Stream	Initial Records	Filtered Records
Web of Science	A—Intelligent chatter management	762	687
Web of Science	B—Sustainability consequences	762	620
Scopus	A—Intelligent chatter management	528	504
Scopus	B—Sustainability consequences	2418	2263
Total search hits		4470	4074
Web of Science	Combined A OR B	-	976
Scopus	Combined A OR B	-	2304
Combined database records Before cross-database deduplication		-	3280

Note: Individual stream counts include overlapping records. The combined A OR B results remove within-database overlap (331 records in Web of Science and 463 in Scopus). The final combined count of 3280 has not been deduplicated across databases.

The searches were complemented by targeted identification of foundational contributions and backward and forward citation tracking. The curated evidence collection comprised 30 primary studies for detailed technological and sustainability assessment, 16 previous reviews for contextual comparison, and

two adjacent machining-vibration studies retained for supplementary interpretation. The primary studies were classified according to machining process, technological approach, validation methodology, sustainability outcomes, evidence basis, and SEL.

The reported database searches were conducted during manuscript revision to document the search strategy and its retrieval characteristics. The original record-level screening histories and cross-database deduplication records were not preserved. Accordingly, the curated evidence collection is not presented as the final sample of a fully documented PRISMA systematic review.

2.3. Eligibility Criteria and Study Selection

Eligible primary studies comprise peer-reviewed journal articles and conference papers published between 2010 and 2026 that address machining chatter in milling, turning, boring, micro-machining, robotic machining, or related subtractive manufacturing processes. Foundational pre-2010 studies are retained selectively where necessary to establish key theoretical developments, benchmark methods, or historically important concepts. Review articles are used for contextual comparison and citation searching but are not treated as primary evidence in the SEL assessment.

Studies are included when they make a substantive contribution to chatter modelling, prediction, monitoring, detection, learning-based analysis, digital-twin development, chatter avoidance or suppression, adaptive control, or the quantification of manufacturing and sustainability-related outcomes. Studies focused on additive manufacturing, grinding, general fault diagnosis, or vibration control without a specific chatter-management objective are excluded from the principal synthesis. Vibration-assisted machining studies are likewise excluded unless chatter prediction, avoidance, detection, or suppression constitutes an explicit part of the investigation. Duplicate reports and non-technical publications are excluded, as are records for which sufficient methodological information is unavailable to establish eligibility.

The identification and selection of studies were guided by the eligibility criteria described above. The database searches yielded 976 distinct records within Web of Science and 2304 within Scopus after filtering and combining the two search streams, as reported in Table 1. These counts represent database-level retrieval results before cross-database deduplication and should not be interpreted as the number of studies included in the final synthesis. The curated evidence collection comprised 30 primary studies selected for detailed technological and sustainability assessment, together with 16 previous reviews used for contextual comparison and two adjacent machining-vibration studies retained for supplementary interpretation. The primary studies were characterized according to their technical relevance, methodological characteristics, validation approaches, and sustainability-related outcomes. Because the original record-level screening histories and cross-database deduplication records were not preserved, the study-selection process cannot be reconstructed as a complete PRISMA flow diagram. The synthesis is therefore interpreted as a structured critical assessment of the curated evidence base rather than an exhaustive systematic assessment of all retrieved records.

2.4. Data Extraction and Coding

Study-level extraction records bibliographic details, machining process, material and geometry, physical model, sensors, signal processing, learning method, and control strategy. Deployment fields distinguish offline analysis, online operation, demonstrated real-time capability, and validation across operating conditions or machine–tool–workpiece configurations [7,24–27]. These fields allow technological characteristics and deployment maturity to be evaluated separately from sustainability performance.

Outcome fields cover energy or power, tool wear and life, surface integrity, productivity, machining time, scrap, rework, material loss, component durability, and environmental impacts. Each outcome is classified by SEL and separately identified as measured, modelled, or assumed/inferred. This separation supports comparisons across studies with different technologies and validation conditions.

2.5. Sustainability Evidence Level (SEL) Framework

The five-level SEL framework classifies the directness and scope of reported sustainability-related outcomes, independently of algorithmic complexity (Table 2). SEL-0 denotes an asserted sustainability benefit without quantified evidence, whereas SEL-1 requires quantified process-quality proxies, such as vibration, stability margin, or surface roughness. SEL-2 requires at least one quantified resource or manufacturing-performance outcome, including energy consumption, tool wear or life, machining time, or material removal rate (MRR). Signal energy used for chatter detection remains a diagnostic proxy [34], whereas quantified changes in MRR or control-energy requirements provide SEL-2 evidence [35,36]. SEL-3 requires the joint quantitative evaluation of at least two distinct sustainability-relevant outcome dimensions, including trade-offs among productivity, quality, wear, and energy [12,37,38]. SEL-4 requires explicit quantification of environmental impacts, such as carbon emissions or life-cycle impacts.

Study-level classification follows an outcome-based procedure. First, reported outcomes are identified and distinguished from anticipated or inferred benefits. Second, outcomes are categorized as process-quality proxies, direct resource or manufacturing-performance indicators, or environmental impacts. Third, each study is assigned the highest SEL level supported by its reported evidence. Multiple diagnostic indicators alone do not justify SEL-3, while environmental objectives without quantified impacts do not qualify for SEL-4. Ambiguous cases are classified conservatively based on explicitly documented results.

These levels describe outcome coverage and environmental directness, not overall scientific quality or certainty. A scenario-based life-cycle assessment (LCA) may reach SEL-4 despite substantial uncertainty [15]. Each classification is therefore accompanied by its measured, modelled, or assumed evidence basis and the separate methodological appraisal described in Section 2.6.

The industrial key performance indicators (KPIs) included in Table 2 provide an operational link between SEL classifications and measurable manufacturing or environmental outcomes. However, proxy indicators such as MRR, vibration amplitude, and surface roughness cannot independently establish resource savings. For example, increased MRR may reduce machining time, but a reduction in energy consumption or material waste must be verified through corresponding energy, scrap, or rework measurements. Similarly, higher SEL classifications require explicitly quantified outcomes rather than inferred sustainability benefits.

Table 2. SEL framework for classifying the strength and directness of sustainability evidence in machining chatter studies.

Level	Definition	Typical Evidence	Representative Industrial KPIs and Supporting Studies
SEL-0	Sustainability benefit asserted or implied only	A study argues that chatter detection, suppression, or improved stability could enhance sustainability, but no sustainability-relevant manufacturing or environmental outcome is quantified.	No quantified sustainability KPI. Benefits remain asserted or inferred.
SEL-1	Manufacturing proxy quantified	Chatter-related changes in vibration, stability margin, surface roughness, dimensional accuracy, cutting force, or similar process-quality indicators are quantified, but their resource or environmental consequences are not directly evaluated.	Vibration amplitude, chatter severity, stability margin, surface roughness, dimensional error, and cutting-force variation.
SEL-2	Direct resource or manufacturing-performance outcome quantified	At least one sustainability-relevant outcome such as energy/power consumption, tool wear or tool life, machining time, material removal rate, productivity, rework, scrap, or component durability is quantitatively evaluated.	Energy consumption (kWh/part), machining time (min/part), MRR (cm ³ /min), tool life (min), tool consumption (tools/1000 parts), and scrap rate (%). Examples: [8,10,35,36].

SEL-3 Multiple sustainability-relevant outcomes quantified or jointly optimized	Two or more resource, productivity, quality, or life-cycle-related outcomes are evaluated together, or a multi-objective optimization explicitly balances several sustainability-relevant criteria under chatter constraints.	Joint assessment of specific cutting energy (J/mm^3), tool wear, surface roughness (R_a), machining time, and productivity. Examples: [12,37,38].
SEL-4 or life-cycle assessment	Environmental impact is quantified using indicators such as carbon emissions, material footprint, life-cycle energy, or formal/screening-level life-cycle assessment.	Carbon footprint ($\text{kg CO}_2\text{-eq/part}$), material footprint (kg/part), life-cycle energy (MJ/part), and other quantified LCA impact indicators. Examples: [11,15].

2.6. Methodological Appraisal

Methodological appraisal was organized around six independent dimensions rather than an aggregate score: experimental validation, baseline comparison, reporting transparency, generalization, physical credibility, and deployment relevance. Experimental validation was assessed by whether the findings were supported by numerical simulations, hardware-in-the-loop testing, or physical cutting experiments [39,40]. Baseline comparison examined whether the proposed method was evaluated against an appropriate conventional, uncontrolled, or alternative approach under comparable conditions [41,42]. Reporting transparency considered the availability of machining parameters, sensor configurations, data-processing procedures, model specifications, and independent training and test datasets.

Generalization was assessed according to the diversity of operating conditions, tools, materials, workpiece geometries, or machine configurations included in validation, distinguishing within-condition testing from evaluation under previously unseen conditions [43,44]. Physical credibility examined whether the reported models, predictions, and interpretations were consistent with established machining dynamics, including regenerative effects and structural behavior, without automatically penalizing purely data-driven approaches. Deployment relevance considered computational latency, sensing requirements, controller integration, and demonstrated online or real-time operation [45,46].

For each study, the six dimensions were evaluated individually using the methodological details and validation results reported in the publication. Evidence was distinguished as demonstrated, partially supported, or not established, with insufficiently reported information treated as unverified rather than assumed. No composite quality score was calculated, thereby avoiding arbitrary weighting of dimensions. The appraisal remained independent of SEL classification, since a technically well-validated monitoring approach may report only manufacturing proxies, while a study quantifying environmental impacts may still involve substantial methodological uncertainty.

3. Physical Origins and Sustainability Consequences of Machining Chatter

3.1. Regenerative Chatter and Machining Dynamics

For the purposes of this review, machining chatter is treated primarily as a regenerative dynamic instability arising from the interaction between the structural dynamics of the machine–tool–workpiece system and the time-delayed cutting process. Although other mechanisms, including mode coupling and friction-related instabilities, may occur, regenerative chatter remains the dominant framework for stability analysis in turning and milling and underlies most contemporary chatter-prediction, monitoring, and control strategies [47]. The essential mechanism is that vibration generated during a previous tool pass leaves a waviness on the machined surface. When the cutting edge encounters this surface again, the previous vibration modifies the instantaneous chip thickness and therefore the dynamic cutting force, closing a feedback loop between structural motion and chip formation.

In its simplest scalar form, the regenerative contribution to chip thickness may be represented as

$$h(t) = h_0 + y(t - \tau) - y(t), \quad (1)$$

where h_0 is the nominal chip thickness, $y(t)$ is the scalar relative tool–workpiece displacement in the relevant cutting direction, and $y(t - \tau)$ is its delayed value inherited from the preceding pass. The delay τ is associated with the revolution period in turning or, in conventional milling, with the tooth-passing interval. The difference between the delayed and current vibration determines the dynamic modulation of chip thickness. Depending on the phase relationship, the cutting force can remove energy from the structural vibration or feed energy into it, resulting in self-excited oscillation. Contemporary milling models extend this basic mechanism to intermittent engagement, multiple teeth, nonuniform pitch, multiple delays, and multiple structural modes [48].

At the system level, the same mechanism can be represented generically by a delayed dynamic equation,

$$\mathbf{M}\ddot{\mathbf{x}}(t) + \mathbf{C}\dot{\mathbf{x}}(t) + \mathbf{K}\mathbf{x}(t) = \mathbf{F}[\mathbf{x}(t), \mathbf{x}(t - \tau)], \quad (2)$$

where $\mathbf{x}(t)$ is the vector of current structural displacements, $\dot{\mathbf{x}}(t)$ and $\ddot{\mathbf{x}}(t)$ are the corresponding velocity and acceleration vectors, $\mathbf{M}$, $\mathbf{C}$, and $\mathbf{K}$ denote the mass, damping, and stiffness matrices, respectively, and $\mathbf{F}$ is the cutting-force vector. The delayed state $\mathbf{x}(t - \tau)$ represents the structural displacement inherited from the preceding tool pass. Accordingly, the cutting-force depends on both the present and delayed system states. This formulation emphasizes two features that are particularly important for the remainder of this review: chatter depends simultaneously on structural flexibility and on the feedback generated by material removal. It is therefore neither exclusively a machine-structure problem nor exclusively a cutting-force problem.

Structural flexibility is commonly represented through modal parameters or frequency-response functions at the tool–workpiece interface. Natural frequencies, modal stiffnesses, damping ratios, mode shapes, and their orientation determine how strongly the cutting system responds to dynamic forces. Turning stability has been shown to depend on the modal properties of both the tool and workpiece, as well as on their associated vibration directions [49]. In milling, receptance-based approaches similarly use tool-point frequency-response functions to relate structural dynamics to stability predictions [50]. These properties should not be assumed constant in every application. In thin-walled machining, material removal alters workpiece mass and stiffness along the tool path, producing time-varying modal properties and therefore time-varying stability boundaries [51]. In high-speed micro-milling, spindle rotation itself can alter dynamic stiffness and damping through bearing, centrifugal, and gyroscopic effects, requiring speed-dependent frequency-response functions rather than a single stationary structural model [52].

The second central physical component is the relationship between dynamic chip thickness and cutting force. Mechanistic chatter models generally express incremental cutting forces through cutting coefficients that relate chip load to tangential, radial, and sometimes axial force components. These coefficients therefore directly determine the feedback gain of the regenerative loop. Their uncertainty or variation can materially shift the predicted stability boundary. The evolution of cutting-force coefficients with tool wear has been modelled and shown to produce time-varying chatter stability in turning [53]. Such effects are important because stability lobes calculated from fixed coefficients and fixed modal parameters can become progressively less representative as the cutting system evolves during production.

Process damping provides an additional stabilizing mechanism, particularly at relatively low cutting speeds. It arises principally from interaction between the tool flank face and the undulated workpiece surface generated by vibration, producing a force component that opposes motion. Its magnitude depends on vibration wavelength, clearance geometry, cutting speed, and tool condition. Experimental studies have demonstrated that modifying the flank contact can substantially alter machining stability. Appropriately designed flank textures have been shown to enhance process damping and improve the chatter limit in turning [54], while anti-vibration edge geometries can increase process damping in thin-walled Ti-6Al-4V milling [55]. Flank wear itself may also increase process damping and expand the stable depth of cut under

some milling conditions, indicating that tool wear can simultaneously degrade cutting performance and alter dynamic stability [56]. More recent modelling has therefore increasingly incorporated the coupled effects of tool wear and nonlinear process damping rather than treating structural damping as the only dissipation mechanism [57].

The interaction of regenerative delay, structural modes, cutting coefficients, and damping is conventionally summarized through stability-lobe diagrams (SLDs), most commonly expressed in terms of spindle speed and limiting depth of cut. The lobed structure results from the changing phase relationship between successive surface waves as spindle speed alters the regenerative delay. Stable pockets may therefore exist at relatively high depths of cut even when neighboring spindle speeds are unstable. However, the apparent simplicity of the SLD conceals considerable model dependence. Multiple structural modes, multiple regenerative delays, process damping, tool wear, and nonlinear effects can significantly alter both the position and shape of the stability boundary. Joint consideration of process damping, multiple modes, and multiple delays has been shown to improve the prediction of titanium-alloy milling stability [48]. Nonlinear process damping and tool wear can also produce finite-amplitude stability regions that are not captured by a conventional single-boundary SLD [57]. Nonlinear models of flexible plate milling similarly show transitions among periodic, quasi-periodic, and chaotic responses that cannot be fully described by a simple linear stability boundary [58].

Accordingly, the role of machining physics in this review is not to provide an exhaustive derivation of chatter theory, but to establish the variables that later intelligent systems must observe, infer, or update. Regenerative delay determines the feedback mechanism; modal properties determine structural susceptibility; cutting coefficients determine force sensitivity; process damping modifies effective dissipation; and their combined interaction defines the stability boundary. Their dependence on spindle speed, tool condition, workpiece geometry, and material removal also explains why a stability model established before machining may become inaccurate during production. This physical variability is one of the principal motivations for online monitoring, model updating, physics-informed learning, and digital-twin approaches examined in later sections.

3.2. Chatter, Cutting Forces and Process Power

The energetic consequences of chatter originate primarily from its effect on dynamic cutting forces. For a simplified cutting process, the mechanical cutting power can be expressed as

$$P_c(t) = F_c(t) v_c(t), \quad (3)$$

where F_c is the cutting-force component acting in the cutting-velocity direction and v_c is the corresponding cutting speed. Under nominally stable conditions, the force variation is dominated by chip formation and, in milling, periodic tooth engagement. Once regenerative chatter develops, the dynamically varying chip thickness introduces additional force oscillations and can substantially increase cutting-force amplitudes, particularly in structurally flexible systems. Thin-wall milling experiments, for example, have shown more pronounced chatter and force fluctuations in regions of lower structural rigidity [59].

Force fluctuations affect mechanical power, but force amplitude alone does not establish total electricity consumption [60]. Cutting power concerns tool–workpiece interaction; spindle power also includes drive and transmission effects; and machine-tool electrical power includes feed drives, controls, cooling, and auxiliary systems [61]. Dynamic compliance and chatter limits can restrict usable spindle capacity even when sufficient rated power is installed [49,62].

A broader quantity is machine-tool electrical power, P_{MT} , which represents electricity drawn by the complete machine rather than only the mechanical cutting process. It may include the spindle drive, feed axes, controller, pumps, cooling or lubrication systems, and other auxiliary loads. Consequently,

$$P_{MT} \neq P_c, \quad (4)$$

Machining simulation combined with a validated machine-tool power model has been used to examine chatter-related electricity demand [8]. Position-oriented monitoring has also combined spindle power, cutting force, and acceleration in thin-wall machining [63].

The distinction becomes even more important when moving from power to total process energy. For a machining operation of duration T ,

$$E_{\text{process}} = \int_0^T P_{\text{MT}}(t) dt. \quad (5)$$

Thus, total energy depends on both power and duration. Higher stable material removal rates can shorten a cycle despite increased instantaneous power. Numerous-flute and trochoidal milling strategies illustrate how stability-aware tooling and tool paths expand productive cutting conditions [64,65]; their net energy benefit still depends on the chosen system boundary and cycle duration.

A complementary measure is specific energy, which normalizes energy or power by useful material removal. Depending on the adopted system boundary, it may be expressed generically as

$$u = \frac{E_{\text{process}}}{V_{\text{rem}}}, \quad (6)$$

or, for cutting-specific energy,

$$u_c = \frac{P_c}{Q}, \quad (7)$$

where V_{rem} is the removed material volume and Q is the material removal rate. Specific energy compares energy demand with useful material removal [61]. Chatter-free parameter optimization can balance energy and machining time [9], while joint evaluations of cutting energy, wear, and surface finish reveal trade-offs that a single metric can conceal [12].

Physics-informed chatter detection using modal information and process signals [66] should likewise be distinguished from an assessment of manufacturing energy consumption. Signal energy, energy entropy, and phase-based diagnostic factors identify chatter but do not measure manufacturing electricity consumption [67,68].

Active-control energy should also be included within the assessment boundary. Improved chatter suppression can increase the critical milling depth while reducing the energy required by the control system relative to alternative control strategies [36]. Net energy performance should therefore account for both the machining process and the energy consumed by the intervention system.

3.3. Chatter and Tool Degradation

Tool degradation constitutes one of the clearest pathways through which machining chatter can generate both economic and resource penalties. Under stable cutting, the cutting edge is subjected to relatively repeatable mechanical and thermal loading determined by chip formation, friction, cutting speed, and engagement conditions. Regenerative chatter superimposes large-amplitude oscillations on this loading. The resulting fluctuations in chip thickness produce corresponding variations in cutting force, tool displacement, and tool–workpiece contact conditions, increasing the severity and irregularity of the loads transmitted through the cutting edge. Experimental and analytical studies have consequently linked machining vibration with accelerated wear and shortened tool life [10,69].

The mechanical pathway is particularly important. During chatter, instantaneous cutting forces may alternate substantially around their nominal values as the regenerative waviness changes the undeformed chip thickness from one engagement to the next. In milling, where cutting is already intermittent, this modulation can intensify repeated loading and unloading of the cutting edge. Under sufficiently severe instability, loss and re-establishment of effective tool–workpiece contact may also occur, producing highly nonuniform loading conditions. Such oscillatory loading increases the potential for localized edge damage,

micro-fracture, coating degradation, and eventual tool breakage, particularly when combined with the high stresses associated with difficult-to-machine materials. Cutting-tool vibration parameters have been explicitly related to fatigue strength and tool life, indicating that the tool's dynamic loading history contributes to wear progression beyond the effects of nominal cutting parameters alone [69].

Thermal effects provide a second degradation mechanism. Chatter-induced force and contact fluctuations may modify frictional conditions and heat generation at the tool–chip and tool–workpiece interfaces. Consequently, the cutting edge can experience repeated thermal–mechanical variations superimposed on the normal machining temperature field. Chatter stability, cutting forces, surface condition, and tool wear have been shown to vary with the cooling and lubrication regime in turning [70]. Comparisons between wet and minimum-quantity-lubrication conditions indicate that the interactions among temperature, friction, wear, and dynamic stability are influenced by the tribological environment. However, relatively few studies directly isolate chatter-induced thermal–mechanical cycling as a wear mechanism. It should therefore be regarded as a physically plausible pathway rather than a universally quantified consequence of chatter.

Tool wear also feeds back into the dynamics of the machining process. As flank wear, edge radius, or tool geometry evolves, the cutting-force coefficients and contact conditions change, thereby modifying the regenerative feedback responsible for chatter. Wear-dependent process damping has been incorporated into micro-milling stability prediction, showing that progressive tool wear can produce time-varying chatter stability [71]. Experimental evidence from ultra-precision fly cutting similarly indicates that increasing tool wear alters chatter stability and can increase the tendency toward instability under specific operating conditions [72]. Wear-induced changes in cutting-force coefficients have also been represented as a time-varying process, directly linking tool degradation to the evolving reliability of chatter-stability predictions [53]. In micro-milling, this interaction has been extended through models that incorporate tool wear, runout, size effects, and regenerative chip thickness, with validation using Ti-6Al-4V cutting experiments [73].

The interaction is not, however, universally monotonic. Increased wear does not necessarily reduce dynamic stability, because chatter stability and tool wear describe different physical states of the machining system. Chatter stability concerns whether the coupled tool–workpiece system remains resistant to self-excited vibration under a given set of operating conditions, whereas tool wear concerns the progressive degradation of the cutting edge and its remaining functional capability. Flank wear enlarges the contact region between the tool flank and the newly generated surface, thereby enhancing process damping, particularly at lower cutting speeds. Experimental evidence indicates that increasing flank wear can enlarge the stable depth of cut in milling through stronger flank–workpiece interaction [56]. Tool wear and nonlinear process damping have also been shown to interact in determining finite-amplitude chatter stability [57]. A worn tool may therefore become more dynamically resistant to chatter under certain conditions even while its cutting edge is physically deteriorating, its remaining useful life is decreasing, and its tribological or surface-performance characteristics are worsening. Improved chatter stability should therefore not be interpreted as improved tool condition, and increased tool wear should not be assumed to imply reduced stability. The two indicators capture different aspects of process performance and may evolve in opposite directions.

Recent experimental evidence further indicates that the interaction can also operate in the opposite direction, with progressive tool wear contributing to undesirable vibration. In precision turning of NAK80 with cubic boron nitride tools, increasing flank wear has been shown to alter machining-system vibration and, at advanced wear levels, to promote multimode vibration and chatter-related surface patterns [74]. These observations support a bidirectional degradation mechanism: chatter can accelerate tool degradation, while progressive tool wear can modify cutting forces, contact conditions, and system dynamics, thereby altering the susceptibility of the machining process to chatter. This closed-loop interaction between chatter, tool degradation, and evolving process dynamics is summarized in Figure 1.

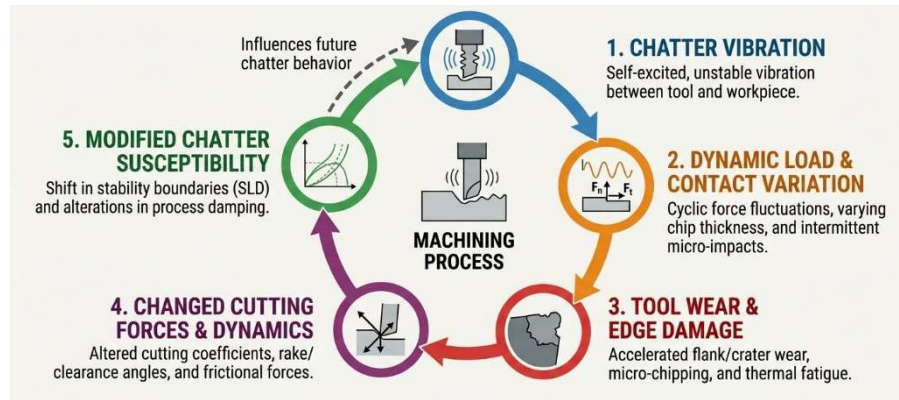


Figure 1. Closed-loop interaction between machining chatter and tool wear. Chatter-induced dynamic loading accelerates tool wear and edge damage, while progressive wear alters cutting forces, contact conditions, and process dynamics, thereby modifying subsequent chatter susceptibility and stability boundaries.

This coupling matters for monitoring because signals obtained with a fresh tool may not represent later wear states. Control strategy also affects tool-life assessment: variable-speed turning requires appropriate tool-life models [75], while adaptive feed control can account for excessive loads, wear, and chatter [76].

Shorter tool life increases replacements, tooling resources, and downtime. Sustainability assessment should therefore quantify the wear rate, useful life, or tools consumed per production volume. Vibration reduction alone cannot establish these outcomes, especially when wear and dynamic stability change in different directions.

3.4. Chatter and Surface Integrity

Surface integrity includes roughness, waviness, dimensional accuracy, and the near-surface material state. Chatter changes the relative tool–workpiece trajectory, making vibration and stability relevant to surface prediction. Studies incorporating these variables have improved roughness estimation beyond models using nominal cutting parameters alone [23,77,78]. Tool modifications, piezoelectric intervention, and shear-thickening fluid damping have also been linked to vibration suppression and improved finish [79–81].

Roughness and waviness require separate assessment. Thin-wall milling studies quantify both [82], while face-hobbing analysis relates chatter frequency to spatial surface patterns [83]. Acceptable average roughness therefore does not necessarily exclude periodic waviness. Dimensional errors additionally reflect static deflection and forced vibration. Joint stability and surface-location-error models and optimization address these interacting constraints [84,85]; digital-twin monitoring and adaptive spindle-speed control extend them toward online intervention [86,87].

Evidence concerning residual stress, microhardness, and subsurface modification remains comparatively limited. Surface-integrity changes under different stability conditions have been linked to fatigue behavior in Ti-6Al-4V [13]. Broader machinability studies also report near-surface modifications, although these effects cannot always be attributed specifically to chatter [88]. The implications of such changes for component service life are discussed in Section 3.7.

These measurements characterize manufacturing quality. Their resource significance depends on whether changes alter finishing requirements, tolerance compliance, rejection, or component life. The distinction between surface indicators and downstream outcomes is maintained in the SEL assessment.

3.5. Chatter, Scrap and Rework

The material-waste consequences of chatter can be represented through a pathway linking machining instability to quality deterioration, corrective processing, and ultimately material loss.

The first links in this pathway are well established. Regenerative vibration can deteriorate surface roughness and waviness, increase dimensional and surface-location errors, and thereby compromise part

quality. When these deviations exceed specified tolerances, additional finishing or corrective machining may be required, while severe defects can result in rejection of the component. This risk is particularly important for large, thin-walled, and high-value parts, where substantial material, machining time, and tool resources may already have been invested before instability develops [89,90]. In large-part milling, severe chatter has been reported to cause simultaneous scrapping of the cutting tool and workpiece, together with pronounced vibration marks and degraded surface quality [91]. The resulting progression from chatter-induced instability through quality loss and rework to eventual scrap and material waste is summarized in Figure 2.

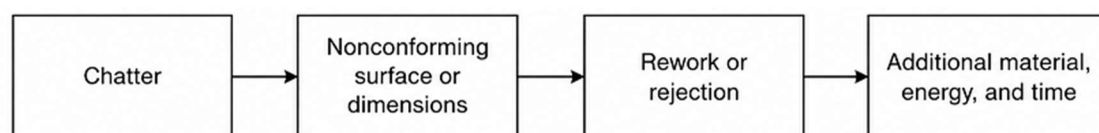


Figure 2. Chatter-induced pathway from machining instability to rework, scrap, and material waste. Chatter degrades surface quality and dimensional accuracy, potentially requiring corrective machining or causing component rejection, thereby increasing material loss, additional processing, and associated resource consumption.

However, most chatter studies stop at upstream indicators such as vibration amplitude, surface quality, or stability improvement. Although some papers explicitly mention workpiece scrap, material waste, or rejection as practical consequences of chatter, they rarely quantify scrap rate, rework frequency, discarded material mass, or additional energy consumption [92,93]. This distinction is important because improved surface quality does not by itself demonstrate a reduction in material or environmental burden.

Direct sustainability evidence would require reporting quantities such as

$$R_s = \frac{N_{\text{scrap}}}{N_{\text{produced}}}, R_r = \frac{N_{\text{reworked}}}{N_{\text{produced}}}, \quad (8)$$

together with the associated material loss, extra machining time, tool consumption, and electricity use. Broader vibration-monitoring research shows that such production-level metrics can be evaluated, including rejected parts and rework time [94].

Accordingly, scrap and rework constitute a credible but poorly quantified sustainability pathway of machining chatter. Under the SEL framework, reductions in vibration or roughness remain proxy evidence unless actual reductions in rejection, rework, or resource use are demonstrated.

3.6. Chatter and Productivity

Chatter constrains productivity because manufacturers often adopt conservative spindle speeds, depths of cut, and feed rates to remain within uncertain stability boundaries. SLDs enable higher-performance parameter selection by identifying combinations of spindle speed and depth of cut that remain chatter-free. Because MRR increases with productive engagement, expanding or effectively exploiting stable operating regions can reduce cycle time and increase throughput. Recent approaches therefore increasingly consider stability and productivity jointly. Machining-time minimization has been combined with chatter and deflection constraints in five-axis blade milling [95], while tool-design optimization has been used to improve system dynamics and increase achievable MRR in large-scale milling [96]. Multi-objective process optimization has also explicitly maximized MRR subject to constraints on chatter, power consumption, tool breakage, dimensional quality, and tool life [97].

However, maximizing productivity does not necessarily maximize sustainable performance. Higher MRR may shorten cycle time but can increase power demand, tool degradation, or quality risk. Sustainable chatter management therefore requires optimization of productivity together with resource and quality constraints rather than maximizing throughput alone.

3.7. Downstream Product-Life Effects

The downstream consequences of chatter remain less extensively investigated than its immediate effects on surface quality, despite their potentially greater implications for component performance and resource efficiency. Chatter-induced waviness, plastic deformation, residual-stress alteration, and surface defects can generate local stress concentrations, thereby influencing fatigue resistance, durability, and in-service performance. Experimental evidence from Ti-6Al-4V milling indicates that increasing chatter severity degrades surface integrity, promotes fatigue-crack initiation at chatter marks, and can reduce average fatigue life by approximately 20% relative to stable machining [13]. Complementary failure analysis has likewise associated machining and chatter marks with stress-concentration sites involved in fatigue-crack initiation, although concurrent metallurgical deficiencies also contributed to the observed failure [98].

The corresponding life-cycle pathway can therefore be conceptualized as manufacturing instability → surface/product degradation → shorter useful life. As illustrated in Figure 3, chatter-induced instability may propagate beyond the machining stage by degrading surface and subsurface integrity, thereby increasing susceptibility to fatigue damage and potentially reducing component service life. Direct quantitative evidence linking chatter-induced manufacturing defects to downstream life reduction, however, remains scarce. Product-life effects should therefore be treated as an important evidence gap rather than as a universally established consequence of chatter.

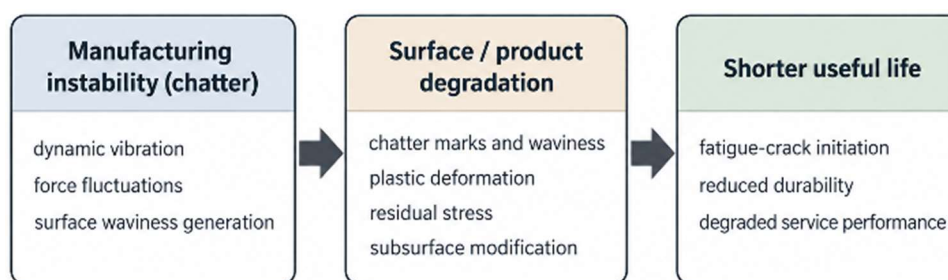


Figure 3. Conceptual life-cycle pathway linking machining instability to reduced useful life. Chatter-induced manufacturing instability can degrade surface and subsurface integrity, thereby increasing susceptibility to fatigue damage and potentially shortening component useful life, although direct quantitative evidence remains limited.

3.8. Environmental and Life-Cycle Evidence

Environmental assessment extends the preceding manufacturing pathways to explicit impact indicators. Chatter stability has been incorporated into low-carbon milling optimization, linking dynamic stability constraints with environmental objectives [11]. Broader dry-milling optimization frameworks have jointly considered machining time, energy consumption, and carbon emissions [99], although such studies provide methodological context rather than chatter-specific environmental evidence. Similarly, carbon-reduction objectives within high-efficiency machining strategies should not be interpreted as demonstrating quantified environmental benefits unless the resulting reductions are explicitly measured or modelled [100]. This highlights the need to distinguish optimization objectives that include environmental terms from studies that actually quantify realized environmental improvements.

Screening-level life-cycle assessment has also been integrated into digital-twin-based stability management, including estimates of material and energy losses associated with scrap generation [15]. Because these estimates partly depend on assumed production and scrap scenarios, the breadth of the environmental assessment should be distinguished from the evidential certainty of its underlying inputs. This distinction between measured, modelled, and scenario-dependent sustainability evidence is synthesized in Section 9.

4. From Physics-Based Chatter Prediction to Intelligent Monitoring

Although closely related, chatter detection, prediction, avoidance, and suppression/control represent distinct functions in machining stability management. Chatter detection identifies the current presence or onset of instability from measured process signals, whereas chatter prediction estimates future instability or stability boundaries using physical models, data-driven approaches, or their combinations. Chatter avoidance selects or adjusts machining parameters to prevent operation in unstable regions, typically using predicted stability information. In contrast, chatter suppression/control involves interventions intended to reduce or eliminate existing or developing chatter, including spindle-speed modulation, adaptive feed adjustment, and active vibration control. These functions may operate sequentially or be integrated within closed-loop intelligent systems, but their objectives and performance indicators differ. Detection is primarily evaluated through classification accuracy and response latency, prediction through stability-boundary accuracy or forecasting performance, avoidance through stable operating conditions and productivity, and suppression/control through vibration reduction, recovery of stable cutting, and intervention effectiveness. Maintaining these distinctions is essential when comparing technological capabilities and their sustainability implications.

4.1. Physics-Based Stability Prediction

Physics-based prediction methods include analytical frequency-domain formulations, numerical delay-system methods, and time-domain simulation [47,50]. Frequency-domain approaches efficiently generate stability boundaries; time-domain models accommodate intermittent engagement, nonlinear contact, and transients at greater computational cost. Semi- and full-discretization methods address periodically time-varying milling dynamics [101,102], while extended formulations include process damping and multiple modes or delays [48,57].

Their interpretability depends on identifiable structural and cutting parameters. Uncertainty in those parameters limits predictive accuracy [18], and the time-varying effects described in Section 3.1 motivate online identification and updating.

4.2. Sensor-Based Chatter Monitoring

Sensor selection balances physical sensitivity, installation burden, bandwidth, and industrial robustness [7]. Cutting-force measurements directly capture force modulation and support time–frequency classification, but dynamometers impose cost and mounting constraints [103]. Accelerometers provide accessible dynamic measurements, with sensitivity to location and structural transmission paths [104].

Internal computer numerical control (CNC) and drive signals reduce external hardware: ball-screw motor current and machine-internal signals have been used to support chatter detection, although their bandwidth and indirect response can limit sensitivity [105,106]. Displacement sensors measure motion directly but face access, coolant, and line-of-sight restrictions; displacement has been combined with acceleration and acoustic pressure in boring [107]. Surface imaging provides information about chatter marks and spatial patterns [108,109], but observation after surface generation can limit early intervention.

Multimodal studies combine sound, acceleration, and cutting-bending-moment features [110], or microphone and accelerometer measurements [111]. Acoustic-emission sensors offer another diagnostic channel by capturing high-frequency cutting and contact phenomena, although coupling and transmission paths affect interpretation [112]. Microphones also support low-cost, non-contact chatter monitoring, with susceptibility to factory noise and positioning [113]. More recent multimodal approaches combine force and acceleration spectra within attention-based networks [114].

Combining sensors introduces synchronization, calibration, and data-bandwidth requirements. Section 5.5 addresses fusion architectures and their contribution beyond individual sensing channels.

Figure 4 illustrates representative vibration-monitoring and chatter-control configurations for turning, milling, thin-wall and micro-milling, and robotic machining. The configurations highlight typical sensor locations, signal acquisition arrangements, and possible control interventions. Although the sensing principles are broadly applicable, sensor placement and intervention strategies depend on process-specific cutting mechanics, structural dynamics, and accessibility. The figure therefore provides an illustrative comparison rather than a representation of specific experimental installations.

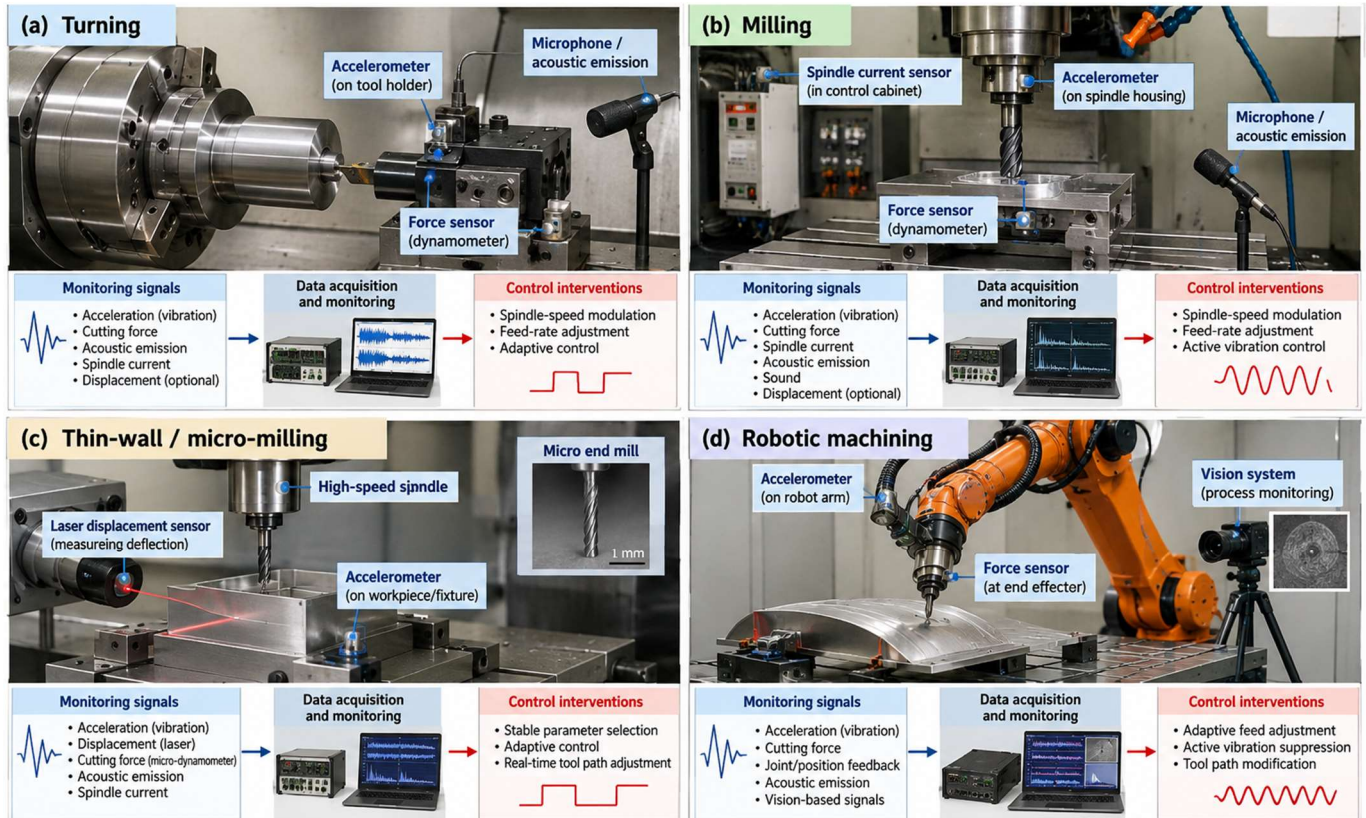


Figure 4. Representative vibration-monitoring and chatter-control configurations for (a) turning, (b) milling, (c) thin-wall/micro-milling, and (d) robotic machining, illustrating typical sensor placements, data acquisition systems, and potential control interventions.

4.3. Signal-Processing Methods

Signal processing provides the intermediate layer between sensor acquisition and chatter classification by transforming raw measurements into representations in which chatter-related characteristics can be identified more effectively. This transformation can be summarized as raw signal $\rightarrow$ chatter-sensitive representation. Classical fast Fourier transform (FFT)-based spectral analysis is effective for identifying dominant frequency components associated with chatter but provides limited temporal localization when instability develops transiently. Short-time Fourier transform analysis introduces time localization through windowed spectral estimation, although the use of a fixed window creates an inherent trade-off between temporal and frequency resolution. Wavelet and wavelet-packet transforms provide multiscale time–frequency localization and have been widely used for signal denoising and the extraction of chatter-sensitive frequency bands [115,116].

For nonlinear and non-stationary signals, adaptive decomposition methods are particularly useful. Empirical Mode Decomposition (EMD) and Ensemble EMD decompose measured responses into intrinsic mode functions, enabling chatter-related components to be isolated before feature extraction [117,118]. Variational mode decomposition provides a more constrained decomposition framework and has been combined with energy entropy, optimized parameter selection, and online energy-ratio indicators for early

chatter identification [119–121]. The Hilbert–Huang transform additionally provides instantaneous time-frequency information and has been combined with wavelet preprocessing for chatter-state identification [115].

Across these methods, spectral energy, entropy, kurtosis, fractal and nonlinear descriptors, and related indicators compress complex sensor data into features suitable for thresholding or intelligent classification. Their principal function is therefore to bridge raw sensing and data-driven decision making, forming the basis for the machine learning/deep learning methods discussed next.

4.4. Limitations of Threshold-Based and Conventional Monitoring

Conventional chatter-monitoring methods often rely on fixed thresholds applied to vibration amplitude, spectral peaks, energy ratios, entropy measures, or other handcrafted indicators. Although such approaches are computationally efficient and physically interpretable, their performance is strongly affected by operating-condition dependence. A threshold calibrated for one spindle speed, depth of cut, tool, or workpiece configuration may not remain valid when process dynamics change [43,106].

Threshold selection itself is therefore a major limitation. Conservative thresholds may generate false alarms during stable but highly dynamic cutting, whereas permissive thresholds may delay detection until chatter has become fully developed. This problem is exacerbated by measurement noise, machine background vibration, transient cutting events, and signal contamination, which can overlap with chatter-related frequency content [110].

Conventional monitoring is also challenged by the early transition from stable cutting to incipient chatter. During this stage, diagnostic features may change gradually and remain close to normal-process variability, reducing the reliability of hard decision boundaries [118,120]. In addition, tool wear, material removal, spindle-speed effects, and changing workpiece flexibility continuously modify the dynamic response, particularly in thin-wall and robotic machining [51,52].

These limitations motivate data-driven approaches that can learn nonlinear decision boundaries and adapt to multidimensional signal patterns. The transition toward machine learning therefore reflects a need for greater robustness, generalization, and sensitivity to evolving process states, rather than merely higher classification accuracy.

5. Machine Learning and Deep Learning for Chatter Intelligence

5.1. Classical Machine Learning

Classical machine learning shifted chatter monitoring from manually calibrated thresholds toward data-driven classification of machining states. Rather than replacing signal processing, these methods generally operate on handcrafted time-, frequency-, time–frequency-, or nonlinear features extracted from force, vibration, acoustic, or machine-internal signals.

Support vector machines have been particularly effective for relatively small experimental datasets and high-dimensional feature spaces. They have been used for in-process chatter discrimination and, when combined with boosting, for improving robustness to varying cutting conditions and mislabeled samples [112,122]. Random forests and boosted trees address feature interaction and nonlinear class boundaries while retaining relatively low computational cost. Yan and Sun [123] used Random Forest for early chatter identification in thin-wall milling, whereas Li et al. [124] employed gradient tree boosting to distinguish chatter severity levels.

Artificial neural networks (ANNs) have been used to map processed sensor features to chatter states and to couple detection with parameter optimization. Signal decomposition and ANN-based prediction have been combined with material-removal-rate optimization [125], while generalized regression neural networks have been applied to stability prediction and process optimization [126]. Feature-based classification approaches,

including support vector machines and gradient tree boosting, offer practical alternatives for chatter recognition by exploiting discriminative features extracted from machining signals [122,124].

Bayesian approaches extend classification toward probabilistic stability estimation and uncertainty-aware updating, while ensemble learning combines multiple learners to improve robustness, generalization, and performance when labeled chatter data are limited [40,122,127]. Nevertheless, most classical machine learning pipelines remain dependent on engineered features and training-condition representativeness, motivating the move toward deep learning and automated representation learning.

5.2. Deep Learning

Deep learning extends chatter intelligence by reducing dependence on manually engineered features and learning diagnostic representations directly from raw or transformed sensor data. Convolutional neural networks (CNNs) are particularly effective for extracting local patterns from time series, spectra, and time–frequency maps. They have been applied to automated chatter-state classification, noise-resistant monitoring, and embedded real-time detection [17,46,103].

Recurrent neural networks and long short-term memory (LSTM) networks are well suited to capturing temporal dependencies in chatter development. LSTM-based monitoring using motor-current signals has demonstrated potential for online chatter detection [105], while hybrid architectures combining LSTM with multiscale convolution have been used to distinguish stable cutting from chatter under more complex dynamic conditions, including beat effects [128].

Autoencoders provide nonlinear representation learning and dimensionality reduction, reducing reliance on extensive manual feature engineering and fully labeled datasets. In thin-wall milling, autoencoder-based feature learning combined with hybrid clustering has been applied to chatter identification, illustrating the potential of partially unsupervised monitoring strategies [129].

Attention architectures further enhance discrimination by assigning greater importance to chatter-sensitive temporal intervals, sensor channels, or learned features. Temporal and channel attention have been integrated for chatter detection in thin-wall milling [130], while attention mechanisms combined with transfer learning have been used to improve detection performance under changing machining conditions [41]. Despite these advances, the practical value of deep-learning approaches depends on their data requirements, generalization across changing machining conditions, interpretability, and demonstrated real-time performance.

5.3. Early Detection and Chatter Severity

Most chatter-monitoring studies formulate the problem as a binary distinction between stable cutting and chatter. This formulation is useful for diagnosis but less suitable for real-time intervention, as corrective action is most effective before fully developed instability occurs.

Recent approaches therefore distinguish three process states: stable cutting, a transition or incipient-chatter stage, and fully developed chatter. Time–frequency features, entropy measures, and learning-based change-detection methods have been used to identify this transition stage before vibration reaches severe levels [118,120,131]. Recognizing this intermediate state provides a more informative basis for timely control decisions than binary classification alone.

A further development is quantitative chatter-severity estimation, in which the output is expressed as a continuous or multi-level measure rather than a simple class label. Severity may be characterized using vibration amplitude, spectral-energy ratios, stability margins, or learned regression outputs.

For intelligent chatter control, early-transition detection and severity estimation are more valuable than post-event classification because they provide sufficient time for spindle-speed, feed-rate, or active-control adjustment before substantial tool, surface-quality, or productivity losses occur.

5.4. Generalization and Transferability

A central limitation of data-driven chatter monitoring is that high classification accuracy within a single experimental dataset does not necessarily indicate industrial usefulness. Random train–test splits often contain signals collected under closely related operating conditions, allowing a model to interpolate within a familiar domain rather than demonstrate genuine generalization.

The reliability of reported classification performance also depends on dataset composition and validation design. Small datasets may inadequately represent variations in cutting conditions, tool wear, and machining dynamics, while class imbalance can inflate overall accuracy when stable cutting dominates the observations. Accordingly, precision, recall, F1-score, and class-specific performance should complement accuracy, particularly for incipient-chatter detection. Random train–test splitting of highly correlated signal windows can introduce data leakage and overly optimistic performance estimates. More rigorous evaluation requires separating training and testing at the level of independent cutting trials, operating conditions, or machine configurations, with feature selection, normalization, and hyperparameter tuning performed exclusively within the training data. Grouped or nested cross-validation can reduce overfitting and improve the reliability of model selection, although cross-validation within a single experimental domain does not establish cross-domain generalization. Validation under previously unseen spindle speeds, cutting depths, tools, materials, workpiece geometries, or machines therefore remains essential for assessing industrial transferability [16,41,43,44,131].

For practical deployment, a chatter model should remain reliable when spindle speed, axial or radial depth of cut, feed, tool geometry, tool overhang, workpiece material, and workpiece geometry differ from those represented during training. These changes modify both process excitation and structural dynamics, causing substantial distribution shifts in measured vibration, force, acoustic, and current signals. The problem is particularly severe in thin wall and robotic machining, where structural properties can evolve with cutting position or material removal [17,51].

Some studies have explicitly addressed generalization across changing machining conditions. Generalized monitoring methodologies have been developed for variable-speed machining [43], while automated feature extraction has been evaluated under varying milling conditions [44]. More demanding validation involves transfer across substantially different process domains. Transfer learning between turning and milling datasets has shown that previously learned representations can reduce dependence on extensive newly labeled data [16]. Transfer learning combined with dynamic-model guidance has also been used to improve chatter recognition under changing operating conditions [41]. More recent validation has considered variations in workpiece, cutting parameters, cutting edges, and tool overhang, indicating a gradual shift toward broader and more demanding evaluation protocols [131].

Nevertheless, cross-machine, cross-material, and cross-geometry validation remains comparatively limited. Models that perform well across spindle speeds on one machine cannot automatically be assumed transferable to another machine with different structural modes, sensors, control systems, or noise environments. Transfer learning, domain adaptation, physics-guided representations, and continual model updating are therefore increasingly important.

Consequently, reported accuracy should be interpreted together with the scope of the validation domain. Industrially convincing evidence requires testing on previously unseen conditions, tools, materials, geometries, or machines rather than only high performance on randomly partitioned samples from the same dataset.

The generalizability of chatter-monitoring and control strategies also depends on fundamental differences between machining processes. Turning typically involves continuous cutting with regenerative delay associated with workpiece rotation, whereas milling involves intermittent tooth engagement, periodically varying cutting forces, and tooth-passing delays [47,48]. Consequently, stability models, signal characteristics, and detection thresholds cannot necessarily be transferred directly between these processes. Micro-milling introduces additional complications associated with size effects, tool runout, wear-dependent

cutting mechanics, and speed-dependent spindle dynamics [52,73]. In thin-walled machining, progressive material removal changes workpiece stiffness and modal properties, producing position-dependent stability boundaries [51]. Robotic machining introduces additional configuration-dependent structural flexibility, further limiting the applicability of fixed stability models and monitoring thresholds.

These differences suggest that the underlying principles of regenerative chatter modelling, time–frequency analysis, machine learning, and adaptive control are broadly transferable, whereas calibrated model parameters, diagnostic features, decision thresholds, and control settings generally require process-specific adaptation. Cross-process transfer learning has shown promising results between turning and milling [16], but this does not establish universal transferability. Similarly, vibration-reduction percentages, detection accuracy, and productivity improvements should not be compared directly across studies with different materials, cutting conditions, machine dynamics, and validation protocols. More convincing evidence of generalization requires validation across previously unseen processes or configurations, with process-specific recalibration and performance degradation explicitly reported [41,43,44,131].

An additional challenge to model generalization is uncertainty in the physical parameters that govern chatter stability. Changes in workpiece material, tool geometry, cutting coefficients, modal stiffness, damping, and tool wear can modify regenerative feedback and shift stability boundaries [18,19,51,53]. Consequently, robustness should be assessed through systematic parameter perturbation rather than solely through prediction accuracy under nominal conditions. Local sensitivity analysis can identify the parameters to which predicted stability is most responsive, while global sensitivity analysis can examine their combined influence over physically plausible ranges. Such analyses are particularly relevant when models are transferred between cutting tools, workpiece alloys, or machine configurations with different dynamic characteristics.

Perturbation-based validation should evaluate model performance across variations in cutting-force coefficients, modal frequencies, damping ratios, tool overhang, and process conditions. Robustness boundaries can be defined as the parameter ranges within which stability predictions, chatter classification, or control performance remain within specified tolerances. Relevant indicators include stability-boundary displacement, classification performance degradation, false-alarm rates, and intervention effectiveness. Testing on previously unseen alloys and tool configurations should additionally distinguish parameter recalibration from genuine model transferability. Although these procedures offer a systematic basis for assessing robustness, quantitative perturbation-based generalization boundaries remain insufficiently established in the reviewed literature. Their development therefore represents an important priority for industrial validation.

5.5. Multimodal Sensing and Sensor Fusion

Fusion architectures differ in where sensor information is combined. Signal-level fusion integrates aligned measurements; feature-level fusion combines extracted descriptors; and decision-level fusion combines model outputs. Deep multimodal networks instead learn joint representations from separate input streams. Examples include multi-sensor feature integration [107,110,111] and a dual-stream attention CNN combining force and acceleration spectra [114].

Evaluation should compare fusion with individual-channel baselines and examine whether improved discrimination persists under noise or changing conditions. Additional channels may provide complementary information or introduce redundancy.

5.6. Algorithmic Performance Versus Manufacturing Performance

Algorithmic evaluation commonly relies on accuracy, precision, recall, and related classification metrics, whereas manufacturing-level evaluation additionally considers detection latency and the effectiveness of subsequent intervention. Studies linking intelligent monitoring to material-removal

optimization [125], closed-loop stability testing [40], or energy–productivity optimization [14] illustrate this transition from diagnostic performance to process-level outcomes. However, high classifier accuracy alone does not demonstrate a sustainability benefit; such claims require explicit evidence of improvements in resource use, productivity, durability, waste reduction, energy demand, or environmental performance.

6. Physics-Informed and Hybrid Intelligence

Physics-informed and hybrid approaches address limitations of purely data-driven chatter models by incorporating machining physics through physically meaningful features, mechanistic baseline models or priors, or explicit training constraints [16,41]. These distinct forms of integration should not be grouped indiscriminately under the term physics-informed machine learning.

6.1. Physics-Guided Features and Hybrid Physics–Data Models

In the simplest form, physical knowledge is introduced through model inputs. Modal frequencies, damping ratios, predicted chatter frequencies, stability margins, and other dynamics-related quantities can provide physical context for sensor-derived features. Modal information obtained from impact testing and finite-element analysis, for example, has been combined with process signals for chatter detection in thin-wall machining [66]. The effectiveness of such features nevertheless depends on the accuracy of the underlying physical characterization and its ability to remain representative as the tool–workpiece system changes.

A stronger integration combines mechanistic predictions with data-driven correction. A generic hybrid formulation can be expressed as

$$y = y_{\text{phys}} + f_{\theta}(\mathbf{x}) \quad (9)$$

where y_{phys} denotes the prediction obtained from a physics-based stability or dynamic model and $f_{\theta}(\mathbf{x})$ learns the residual discrepancy between that prediction and observed machining behaviour. Bayesian updating provides a related strategy in which experimental observations are used to update uncertain model parameters or stability probabilities. Receptance-based learning [50] and Bayesian stability formulations incorporating process damping [18,19] illustrate this class of approaches, while physics-guided stability learning has also been investigated for decision-making under sparse observations [132]. In these formulations, physical knowledge serves as a baseline, prior, or structural guide rather than an explicit constraint in the learning objective.

6.2. Physics-Constrained Learning and Physics-Informed Neural Networks

A more explicit form of integration introduces physical consistency directly into model training. A generic objective can be written as

$$\mathcal{L} = \mathcal{L}_{\text{data}} + \lambda \mathcal{L}_{\text{phys}}, \quad (10)$$

where $\mathcal{L}_{\text{data}}$ measures agreement with experimental observations, $\mathcal{L}_{\text{phys}}$ penalizes violations of known physical relationships, and λ controls the relative contribution of the physical constraint. In chatter applications, such constraints could represent regenerative dynamics, cutting-force relationships, structural response, or stability conditions. This formulation differs conceptually from simply supplying physics-derived features or updating a mechanistic model probabilistically; these approaches should not automatically be described as physics-constrained learning. Moreover, inaccurate or oversimplified physical constraints can introduce systematic bias rather than improve prediction.

Physics-informed neural networks (PINNs) represent a particular form of physics-constrained learning in which governing equations, together with relevant initial or boundary conditions, are incorporated into neural-network training [133,134]. Application to machining chatter would require representation of regenerative delay, structural dynamics, and potentially nonlinear and time-varying tool–workpiece interactions. Such formulations may be useful for state estimation, parameter identification, or prediction

under limited observations. However, their practical advantage over established mechanistic, Bayesian, or hybrid physics–data approaches remains to be demonstrated for delayed, nonlinear, and continuously changing machining systems.

Conventional numerical approaches, including semi-discretization, full-discretization, and time-domain integration, remain established methods for analysing regenerative chatter governed by delay differential equations [101,102]. These methods offer physically interpretable stability predictions and generally provide efficient solutions when governing parameters and machining conditions are sufficiently well characterized. PINNs, in contrast, incorporate governing-equation residuals into the learning process and may offer advantages for inverse problems, sparse-data state reconstruction, and repeated predictions across parameterized operating conditions [133,134]. However, their computational efficiency depends strongly on the application. PINN training can be substantially more expensive than solving a single delay differential equation (DDE), particularly when regenerative delays, rapidly varying cutting forces, or multiple vibration modes must be represented. Once trained, a neural surrogate may support faster repeated evaluations, although this advantage must be demonstrated rather than assumed.

The relative suitability of these approaches therefore depends on the modelling objective. Conventional DDE solvers are generally preferable for well-defined stability analysis under fixed machining conditions, whereas physics-informed or hybrid neural models may be more useful when uncertain cutting coefficients, evolving structural properties, or limited measurements require repeated model updating. Table 3 summarizes the relative strengths and limitations of these approaches across key modelling and computational criteria. Their performance should be compared under varying spindle speeds, depths of cut, tool-wear states, and workpiece stiffness conditions using common benchmarks. Relevant indicators include stability-boundary error, time-response accuracy, computational cost, training time, inference latency, and robustness to previously unseen conditions. Importantly, direct quantitative benchmarks demonstrating consistent PINN superiority over established DDE solvers for machining chatter remain insufficient in the reviewed evidence. Accordingly, PINNs should be regarded as a potentially complementary approach rather than an established replacement for conventional numerical methods.

Table 3. Qualitative comparison of conventional DDE-based methods and physics-informed neural approaches for machining chatter analysis.

Criterion	Conventional DDE-Based Methods	PINNs and Physics-Informed Neural Surrogates
Forward stability analysis	Established methods with well-characterized numerical procedures	Require validation against established numerical solutions
Single operating condition	Generally efficient for well-defined models	Training overhead may outweigh computational benefits
Repeated parameter evaluations	Additional numerical solutions or stability calculations may be required	Potentially rapid inference after training over a parameterized domain
Sparse-data parameter identification	Requires additional inverse or estimation procedures	Can integrate physical constraints with limited observations
Time-varying structural properties	Requires parameter or model updating	Potential for adaptive state and parameter estimation
Accuracy near stability boundaries	Convergence and accuracy can be systematically assessed	Boundary accuracy requires explicit verification
Generalization	Depends on governing-model validity and parameter identification	Limited by training coverage and physical-model assumptions
Computational efficiency	Primarily determined by numerical resolution and problem complexity	Depends on training cost, inference time, and number of repeated evaluations

From a sustainability perspective, physics-supported learning may reduce the number of trial cuts, experimental calibration requirements, and unsafe parameter searches needed to establish stable operating regions. The evidence reviewed here, however, primarily demonstrates improvements in prediction,

identification, or stability assessment. Reductions in tool consumption, material loss, machining time, or energy demand should therefore be quantified directly rather than inferred from improved predictive performance. Such distinctions are particularly important when evaluating these approaches within the SEL framework.

7. Chatter Avoidance, Suppression and Adaptive Control

Monitoring alone does not generate manufacturing or sustainability benefits unless the detected instability leads to an effective intervention. Chatter-management strategies can therefore be distinguished according to whether instability is avoided before machining, suppressed during machining, or controlled adaptively in closed loop.

7.1. Offline Chatter Avoidance

Offline chatter avoidance selects process parameters before cutting so that the planned operating point lies within a predicted stable region. The principal tool is the stability-lobe diagram, which relates spindle speed and limiting axial depth of cut and therefore enables combinations with higher chatter-free material removal rates to be identified [47].

Spindle-speed optimization exploits the lobe structure to move operation from an unstable region to a nearby stable speed rather than simply reducing cutting aggressiveness. Axial-depth optimization similarly determines the largest permissible depth of cut below the stability boundary. These variables can also be optimized jointly with feed, tool geometry, surface-quality constraints, energy objectives, or productivity targets [126].

Offline chatter avoidance can generate substantial manufacturing benefits by enabling higher, more stable material-removal rates while reducing the risk of chatter-induced tool damage and surface-quality deterioration. Tool-design optimization provides an additional route to expanding the stable operating region. Its major limitation is dependence on the accuracy of the precomputed stability model. Changes in tool wear, clamping, workpiece geometry, modal properties, or cutting coefficients can shift the true stability boundary during machining. Consequently, offline optimization is most effective when system dynamics are sufficiently stationary; otherwise, online monitoring and adaptive intervention become necessary.

7.2. Passive Suppression

Passive chatter suppression modifies the tool–machine–workpiece system so that instability is reduced without continuous sensing or feedback control. Its main advantage is operational simplicity because suppression is achieved through mechanical design rather than real-time computation.

Variable-pitch and variable-helix tools modify the phase relationship between successive tooth engagements and can thereby weaken regenerative feedback. Optimization of variable-pitch tool geometry has been shown experimentally to increase the chatter-free axial-depth range [135]. Other tool-based strategies seek to improve process stability by modifying cutting-edge geometry or introducing localized damping [54].

Damping enhancement and vibration absorbers reduce vibration amplitudes by dissipating or redistributing dynamic energy. Tuned mass dampers, dynamic vibration absorbers, damped toolholders, and compliant interfaces can shift resonances or increase effective damping. Structural modification follows the same principle by increasing stiffness, changing modal properties, or redesigning toolholders and fixtures so that critical modes move away from dominant excitation frequencies [27].

For flexible and thin-walled components, support systems can locally increase workpiece stiffness and suppress chatter as material removal progresses. Follow-up support strategies have demonstrated substantially improved stability and higher-quality, high-MRR machining of thin-walled workpieces [136].

Passive methods require little online computation and can be robust once properly designed. Their main limitation is reduced adaptability when tool wear, workpiece geometry, or operating conditions shift significantly during machining.

7.3. Active Suppression

Active chatter suppression modifies the machining dynamics during cutting through controlled actuation. Unlike passive methods, it can respond to changing operating conditions and therefore offers greater adaptability when tool, workpiece, or process dynamics evolve.

Active damping introduces control forces that increase the effective damping of critical structural modes. Piezoelectric, electromagnetic, or other actuators can be integrated into toolholders, workpieces, or machine structures to counter chatter-related vibration. Hardware-in-the-loop investigations have demonstrated the feasibility of actively damping regenerative chatter, while time-delay feedback strategies have substantially enlarged stable cutting regions in experimental studies [36,39].

Spindle-speed variation suppresses regenerative chatter by continuously or periodically modifying the tooth-passing delay, thereby disrupting the phase coherence required for vibration regeneration. Coordinating spindle-speed variation with feed scheduling can maintain productivity while avoiding unstable cutting conditions [137].

Another strategy involves controlled workpiece excitation, in which externally imposed vibration modifies the effective regenerative delay, thereby altering the conditions for chatter development. Chatter reduction through workpiece excitation with time-delay variation has been demonstrated experimentally [138].

Active suppression can therefore provide greater operating flexibility than passive methods, but it introduces actuators, sensors, control hardware, computational requirements, and additional energy consumption. From a sustainability perspective, its value should be assessed through the net manufacturing benefit, including avoided chatter losses as well as the energy and resource burden of the active control system.

7.4. Intelligent Parameter Optimization

Intelligent parameter optimization extends chatter avoidance beyond selecting stable cutting conditions to optimizing overall manufacturing performance. A conventional formulation seeks to maximize productivity, commonly represented by the MRR,

$$\max_{\mathbf{x}} \text{MRR}(\mathbf{x}) \quad (11)$$

subject to chatter-stability and machine-tool constraints, where $\mathbf{x}$ denotes the set of controllable process parameters, such as spindle speed, feed rate, axial depth of cut, and radial depth of cut. Bayesian learning and machine-learning-assisted optimization have been used to identify stable, high-productivity operating regions with fewer experiments than exhaustive parameter searches [40,126]. More advanced formulations combine learning-based optimization with stability constraints while accounting for tool-life, power, torque, and dimensional-quality limitations [97].

For sustainable machining, however, maximizing MRR alone is insufficient because higher productivity may be accompanied by increased energy demand, accelerated tool wear, or deterioration in part quality. A broader formulation therefore considers multiple competing objectives, for example,

$$\min_{\mathbf{x}} [E(\mathbf{x}), t_m(\mathbf{x}), R_a(\mathbf{x}), W_t(\mathbf{x})] \quad (12)$$

subject to chatter stability, dimensional-quality requirements, and machine constraints, where E denotes energy consumption, t_m machining time, R_a surface roughness, and W_t tool wear or consumption. Depending on the application, productivity, scrap generation, and environmental impacts may also be incorporated explicitly as objectives or constraints.

Existing studies demonstrate elements of this broader formulation. Chatter-free parameter optimization has been applied to improve energy efficiency [9], chatter stability has been incorporated into low-carbon

milling optimization [11], and digital-twin-based optimization has combined chatter constraints with energy-efficiency and MRR objectives [14].

The key transition is therefore from chatter-free productivity optimization toward multi-objective resource and environmental optimization. However, integrated frameworks that simultaneously account for stability, energy consumption, tool life, scrap or rework, cycle time, and carbon emissions remain uncommon.

7.5. Reinforcement Learning and Autonomous Control

Reinforcement learning (RL) represents an emerging route from chatter monitoring toward autonomous intervention. Rather than only classifying machining states, an RL agent learns a control policy that selects actions such as spindle-speed adjustment, feed modification, or actuator commands according to observed process states and a predefined reward function.

Recent work has explored RL-based chatter mitigation combined with active vibration control. Actor–critic RL has been integrated with sliding-mode control and an active vibration damper [139]. Such approaches are attractive because they can adapt control actions as process dynamics change rather than relying on a fixed stability map.

Adaptive control is currently more mature than fully autonomous RL. Closed-loop Bayesian stability testing, coordinated spindle-speed/feed control, and digital-twin-based parameter updating have demonstrated real-time adjustment using measured process information [21,40,137]. These approaches progressively close the loop between sensing, prediction, decision, and intervention.

However, RL for chatter control remains at an early maturity level. Much of the evidence is simulation-based or limited to laboratory-scale demonstrations. Reward-function design, safe exploration, real-time computation, robustness to unseen conditions, and transfer between machines remain unresolved. Moreover, improved control performance should not automatically be interpreted as a sustainability benefit unless reductions in energy, tool consumption, scrap, or cycle time are explicitly demonstrated.

The multi-objective formulation in Section 7.4 also applies to control evaluation. Part-level energy, tool consumption, scrap, and emissions should be assessed against a defined baseline, including the additional burden of sensing, computation, and actuation. Section 10 develops the corresponding research priorities.

8. Digital Twins for Sustainable Chatter Management

A digital twin maintains a continuously updated virtual representation of the machining process through bidirectional or recurrent information exchange with the physical system. Its architecture typically integrates the machine tool, sensing infrastructure, process models, data-processing functions, and decision or control modules [20,29]. A static simulation or offline model alone does not constitute a digital twin because it lacks continuing synchronization with the evolving physical process.

Physics-based digital twins represent machining behavior through structural dynamics, cutting-force relationships, and chatter-stability models, whereas data-driven components can estimate process states, identify deviations, or compensate for model uncertainty. Hybrid implementations combine these functions. Continuous or event-driven model updating is particularly important because tool wear, tool replacement, progressive material removal, and changes in boundary conditions can progressively reduce the validity of an initially calibrated model.

Existing applications demonstrate different levels of integration, including digital-twin-assisted chatter monitoring and control [20], physics-driven adaptive milling control [21], and energy–productivity optimization under chatter-stability constraints [14]. Collectively, these studies illustrate a transition from passive process representation toward digital twins capable of supporting prediction, parameter adaptation, and intervention.

For sustainability-oriented chatter management, however, the digital twin must extend beyond predicting whether the process is stable or unstable. Its decision layer should compare feasible operating

conditions in terms of multiple manufacturing and sustainability outcomes, including productivity, surface quality, tool condition, energy consumption, material loss, and, where supported by available data, carbon-related impacts. In this formulation, chatter stability becomes one constraint within a broader multi-objective decision problem rather than the sole performance target. Validation must therefore address not only prediction accuracy and control effectiveness but also the resource and environmental consequences of the resulting interventions. The strength of such sustainability claims should be evaluated separately from the sophistication of the digital-twin architecture itself.

Practical implementation remains constrained by model-update latency, sensor synchronization, model drift, industrial signal reliability, controller interoperability, computational requirements, and the difficulty of transferring configuration-specific twins across machines, tools, workpieces, and operating conditions [29]. Figure 5 presents a proposed architecture for sustainability-oriented chatter management in which dynamic stability information is integrated with quality, tooling, energy, material, and carbon-related indicators. The architecture should be interpreted as a forward-looking synthesis of the capabilities required for sustainable digital-twin operation rather than as a representation of functionality already demonstrated comprehensively in the reviewed literature.

Cross-sector digital-twin applications, including sustainability-oriented waste-management systems [140], provide useful methodological context for integrating operational and environmental information. However, such applications do not constitute evidence of machining-specific sustainability performance and should therefore be treated only as contextual support.

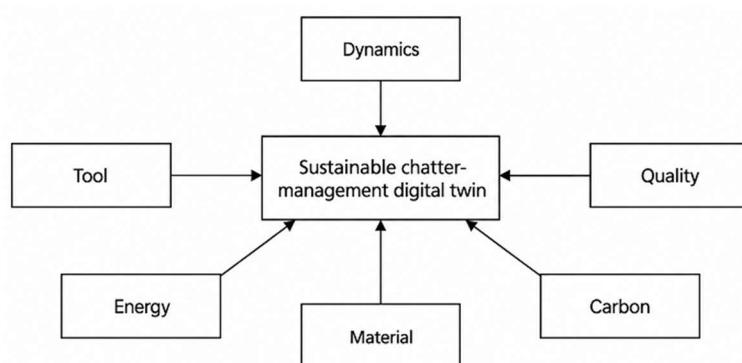


Figure 5. Proposed architecture for a sustainability-oriented chatter-management digital twin integrating machining dynamics, surface quality, tool condition, energy consumption, material use, and carbon-related indicators within an updating decision and control framework.

9. Sustainability Evidence Synthesis

9.1. Sustainability Evidence by Impact Dimension

The sustainability evidence associated with chatter management is unevenly distributed across manufacturing and environmental dimensions. A finalized numerical distribution of SELs requires completion of the formal screening and coding process; accordingly, the synthesis presented here identifies the principal evidence patterns without implying a completed quantitative mapping of the literature.

Productivity, surface quality, and tool-related outcomes are comparatively well represented because MRR, machining time, surface roughness, dimensional accuracy, tool wear, and tool life are routinely evaluated in chatter studies. Evidence concerning energy consumption is less extensive but increasingly available. By contrast, scrap and rework, component durability, carbon emissions, and life-cycle impacts remain sparsely quantified. This imbalance is important because improvements in stability, surface quality, or MRR cannot automatically be interpreted as reductions in resource use or environmental burden. These evidence patterns are summarized in Table 4.

Table 4. Sustainability evidence across key manufacturing and environmental dimensions in chatter-related machining studies.

Sustainability Dimension	Typical Indicators	Current Evidence Status	Main Limitation
Productivity	MRR, machining time, throughput	Relatively strong	Often optimized independently of resource use
Quality	Roughness, dimensional error, surface integrity	Strong	Commonly treated as a manufacturing-performance proxy
Tool life	Wear, tool life, replacement frequency	Moderate–strong	Tool consumption rarely converted to environmental burden
Energy	Power, machining energy, specific energy	Moderate	Machine-level and per-part energy are often not reported
Scrap/rework	Rejection, re-machining, material loss	Weak	Frequently inferred rather than directly measured
Product durability	Fatigue life, residual stress, surface damage	Weak but emerging	Few studies trace chatter effects to measured service-life outcomes
Carbon/LCA	CO ₂ -equivalent emissions, embodied impacts, LCA indicators	Very weak	Rarely integrated directly with chatter experiments or control

The evidence base becomes progressively thinner as assessment moves from conventional manufacturing indicators toward downstream resource and environmental outcomes. This gradient motivates the SEL framework and identifies the dimensions in which additional experimental and life-cycle validation is most needed.

9.2. Technology/Deployment Maturity Versus Sustainability-Evidence Maturity

Technology maturity and sustainability-evidence maturity represent distinct dimensions of chatter-management research. Increasing technological sophistication—from conventional signal processing and sensor-based monitoring toward machine learning, adaptive control, physics-informed intelligence, and digital twins—does not necessarily correspond to stronger evidence of sustainability benefit. As illustrated in Figure 6, several technologically advanced approaches remain supported primarily by manufacturing-performance or resource-related indicators rather than direct environmental or life-cycle evidence.

The matrix should be interpreted as a qualitative synthesis of the reviewed literature rather than a quantitative ranking of individual technologies. Horizontal positioning reflects the relative maturity of the approaches in terms of modelling capability, online implementation, adaptation, and control integration, whereas vertical positioning reflects the type and strength of sustainability evidence represented by the SEL framework. Consequently, a technology may exhibit high implementation maturity while remaining at a comparatively low SEL if its demonstrated benefits are limited to manufacturing proxies or isolated resource indicators.

This mismatch highlights an important research gap: advances in chatter prediction, monitoring, and intervention have progressed more rapidly than their validation in terms of energy, material consumption, component life, carbon emissions, and life-cycle impacts. Explicit carbon and LCA evidence remains particularly scarce and should therefore be interpreted as an emerging evidence category rather than as a characteristic of any specific technology class.

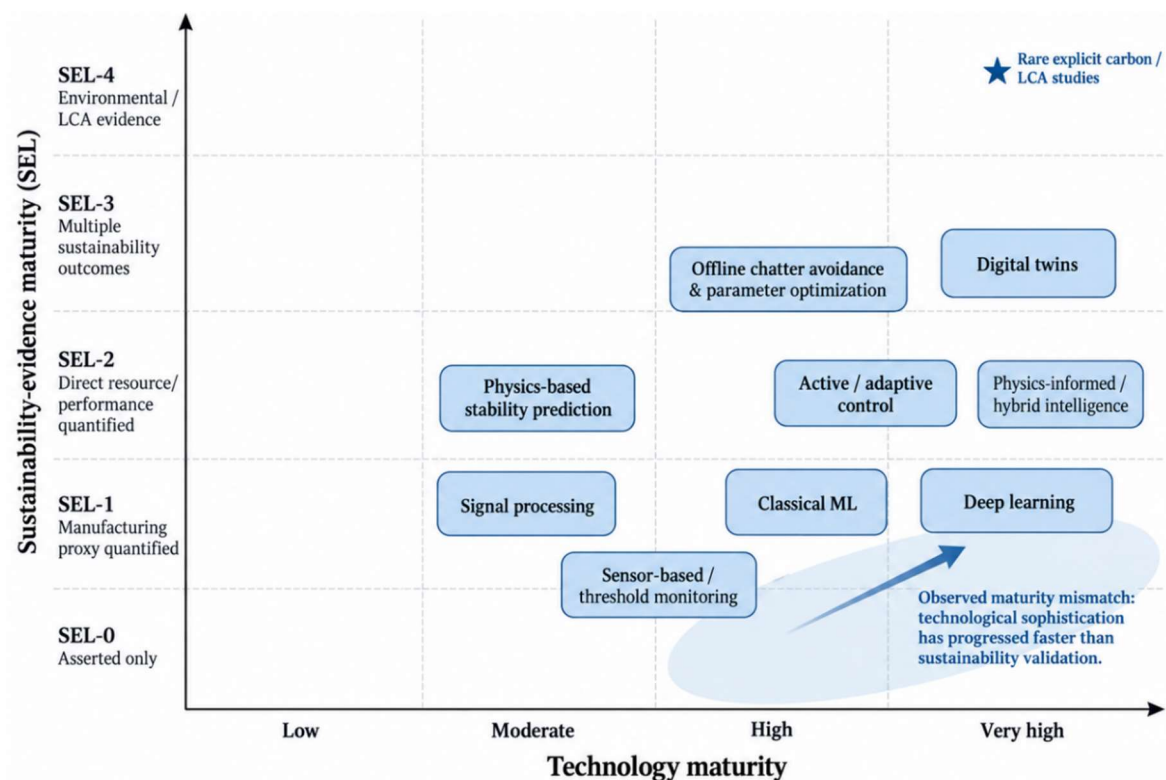


Figure 6. Qualitative relationship between technology maturity and sustainability-evidence maturity (SEL) across chatter-management approaches. The light-blue shaded area and arrow illustrate the mismatch between technological advancement and sustainability validation. The blue five-pointed star highlights the scarcity of explicit carbon-emission and LCA studies and does not represent a quantitatively positioned data point. Technology positions are illustrative rather than quantitatively derived.

To complement the qualitative maturity assessment in Figure 6, Table 5 compares representative studies in terms of machining process, workpiece material, monitoring signals, chatter detection or control approach, validation method, principal performance indicators, and SEL classification. This study-level comparison illustrates how technological capabilities and sustainability-evidence levels differ across chatter-management approaches.

Table 5. Representative studies on machining chatter monitoring, control, and sustainability outcomes, classified according to the SEL framework.

Study	Machining Process/Material	Monitoring Signals/Sensors	Detection or Control Method	Validation	Main Performance Indicators	SEL
Kayhan and Budak [10]	Turning and milling/multiple materials	Tool wear and vibration severity	Experimental stable–chatter comparison	Cutting experiments	Tool wear, tool life	2
Wirtz et al. [8]	Milling/NR	Electrical power, simulated forces	Physics-based simulation and power modelling	Experimental and numerical	Cutting power, machine energy	2
Karandikar et al. [40]	Milling/NR	Stable/unstable cutting outcomes	Bayesian learning and adaptive experimental design	Cutting experiments	Stability, MRR	2
Zhao et al. [73]	Micro-milling/NR	Cutting force, FFT	Physics-based chatter model for digital-twin integration	Experimental	Stability, surface-quality proxy	1
Yesilli et al. [16]	Turning and milling/NR	Vibration time series	Signal decomposition, classification, transfer learning	Experimental datasets	Chatter classification performance	0

Schmitz et al. [50]	Milling/NR	Stability tests, chatter frequency	Physics-supported Bayesian learning	Milling experiments	Stability, maximum MRR	2
Lu et al. [17]	Thin-wall milling/NR	Online machining signals	Interpretable noise-resistant CNN	Experimental	Chatter detection performance	0
Bakhshandeh et al. [20]	Milling/NR	CNC signals, force, acceleration, spindle current	Digital-twin-based monitoring and control	Experimental	Chatter avoidance, process-quality proxies	1
Baruah et al. [12]	Turning/Al 6061-T6	Force, wear, surface finish, energy-related measurements	Experimental parameter investigation	Cutting experiments	Specific energy, wear, surface finish	3
Li et al. [13]	Milling/NR	Roughness, residual stress, microhardness	Comparative stability and surface-integrity analysis	Cutting and fatigue tests	Surface integrity, fatigue life	2
Song et al. [14]	Thin-wall milling/NR	Digital-twin process data	Digital-twin-based parameter optimization	Digital-twin validation	Energy efficiency, MRR	3
Lu et al. [131]	Milling/NR	Cutting force, acceleration	Hybrid CNN and cumulative sum	Comparative experiments	Early chatter detection	0
Huang et al. [21]	Milling/NR	Online cutting force	Physics-informed ML, digital twin, adaptive control	Experimental testbed	Stable cutting, productivity	2
Hu [9]	High-speed milling/NR	Machine power, cutting parameters	Iterative multi-objective optimization	Five-axis milling experiment	Energy utilization, processing time	3
Li and Liu [11]	High-speed multi-pass milling/aluminum alloy	Process and model data	Adaptive particle swarm optimization	Machining case study	Carbon emissions, milling profit	4
Zhu et al. [15]	Ultra-precision micro-milling/NR	Sensor feedback, MTConnect, edge/cloud data	Transfer learning, adaptive digital twin	Experimental and scenario-based LCA	Chatter detection, material and energy losses, environmental impacts	4

NR: Not reported.

9.3. Evidence Basis and Strength of Current Conclusions

SEL should be interpreted together with the basis on which the sustainability outcome is established. Three evidence categories are distinguished: measured, modelled, and scenario-assumed. Measured evidence is obtained directly from experiments or production data, including recorded energy consumption, tool wear, tool life, machining time, scrap generation, or component durability. Modelled evidence is derived using process, energy, carbon, or life-cycle models applied to experimental or operational inputs. Scenario-assumed evidence estimates potential benefits using hypothetical production conditions, literature-derived factors, or assumed reductions in resource use without direct verification in the investigated machining system.

These categories should not be treated as equivalent forms of evidence. Direct measurement provides the closest connection to the investigated manufacturing process, whereas modelled results depend additionally on model validity and input quality, and scenario-assumed outcomes carry further uncertainty associated with the assumptions used. Reporting the evidence basis alongside SEL therefore prevents indirect or assumption-dependent sustainability claims from being interpreted as equivalent to experimentally demonstrated outcomes.

To visualize the distribution of sustainability evidence across the reviewed studies, Figure 7 maps the 30-study curated corpus by SEL classification and sustainability-related outcome dimensions. Most studies are concentrated at SEL-0 to SEL-2 (83.3%), while only five studies (16.7%) reach SEL-3 or SEL-4.

Productivity-related outcomes are the most frequently represented, whereas carbon emissions, life-cycle impacts, and component durability remain comparatively underexplored. The mapping highlights the gap between manufacturing-performance assessment and direct environmental evidence. Because studies may address multiple outcomes and differ in methodological reliability, the figure represents evidence coverage rather than cumulative environmental benefits.

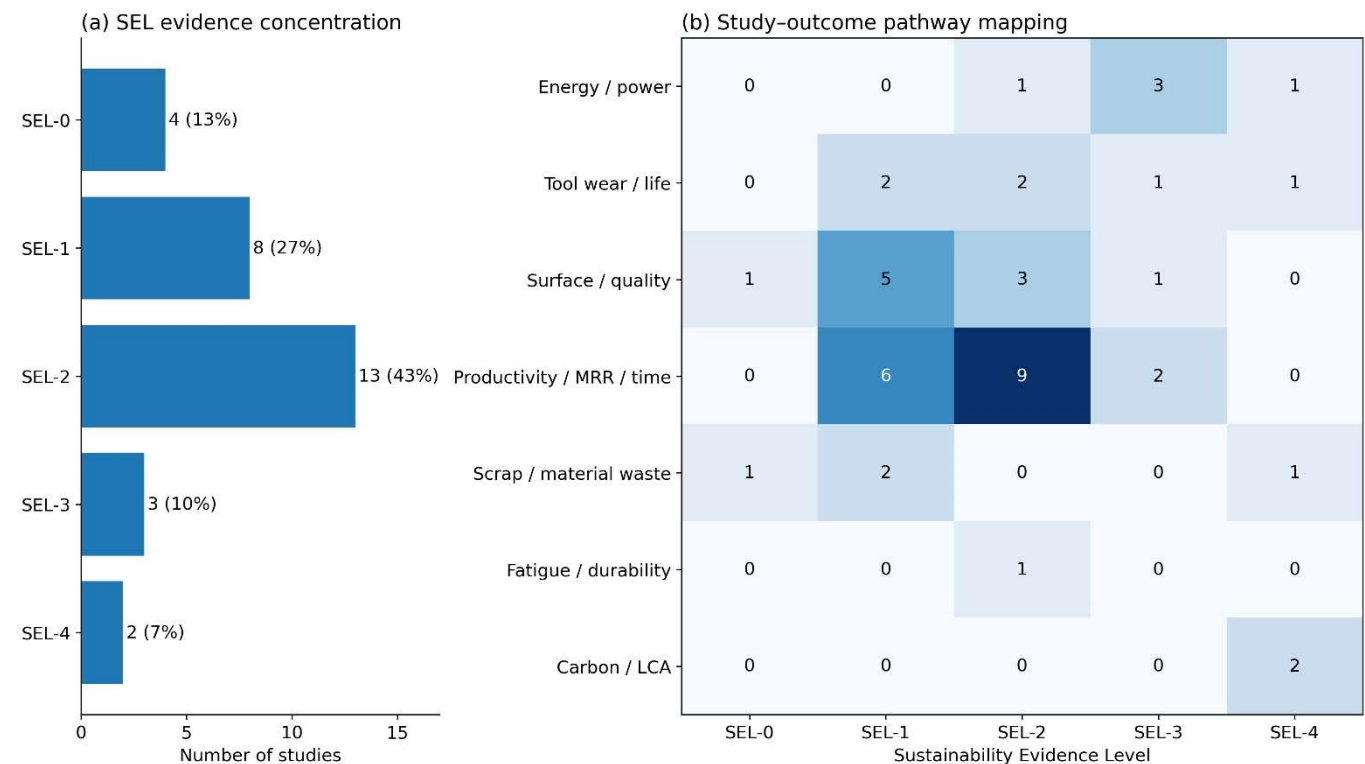


Figure 7. Distribution of SELs and associated sustainability pathways in the reviewed studies ($n = 30$). (a) Study distribution across SEL-0 to SEL-4. (b) Mapping of SEL levels to manufacturing and environmental outcomes, with darker blue shades indicating higher study counts. Cell values indicate study counts, with individual studies potentially contributing to multiple categories. The mapping highlights evidence gaps rather than cumulative sustainability benefits.

10. Closing the Sustainability Evidence Gap: A Research Agenda for Intelligent Chatter Management

The preceding evidence indicates that chatter research has advanced substantially in prediction, monitoring, stability assessment, and control, while validation of the resulting sustainability benefits has progressed more slowly. The next stage should therefore focus on establishing whether technological improvements translate into measurable reductions in manufacturing resource use and environmental burden. Three priorities emerge from the reviewed literature: quantifying the benefits of intervention, demonstrating generalization under realistic operating variability, and extending validation to downstream and life-cycle outcomes.

10.1. From Detection Performance to Quantified Intervention Benefit

Future studies should connect detection and control decisions to measurable changes in machining outcomes such as energy consumption, tool life, cycle time, material loss, scrap, and rework. Early intervention represents a particularly important opportunity. Incipient- and transition-state detection may allow corrective action before chatter develops into severe vibration, tool damage, or unacceptable surface deterioration. However, the practical benefit of acting earlier has rarely been quantified directly. Controlled comparisons among early intervention, conventional intervention, and uncontrolled chatter would help establish whether improved detection timing produces measurable resource or productivity savings.

Future optimization studies should likewise build on the multi-objective formulations discussed in Section 7.4 by incorporating sustainability-relevant outcomes that remain underrepresented, particularly scrap, rework, tool consumption, and carbon-related impacts. The research question should increasingly shift from whether a stable operating condition can be identified to whether the selected condition delivers a demonstrable net benefit at the part or production-system level.

10.2. Generalization and Industrial-Scale Validation

A second priority is validation beyond narrowly defined experimental conditions. Future studies should demonstrate performance across genuinely different operating domains rather than relying primarily on within-dataset validation. Such validation should explicitly distinguish interpolation within familiar parameter ranges from transfer to previously unseen machines, tools, materials, and geometries.

Validation should also progress from short laboratory experiments toward sustained production environments. Longitudinal studies are needed to determine whether monitoring and control systems remain reliable as tools wear, workpieces change, sensors drift, and operating conditions evolve. Relevant reporting should include not only prediction or control performance but also production-scale quantities such as parts produced, interventions executed, tool replacements, downtime, energy consumption, rejected parts, and rework.

Digital twins may provide an effective integration environment for this type of longitudinal assessment, particularly where process state, control decisions, and sustainability indicators must be updated simultaneously. Their value, however, should ultimately be demonstrated through measurable operational outcomes rather than inferred from architectural sophistication alone.

10.3. Extending Evidence to Downstream and Life-Cycle Outcomes

The largest remaining evidence gaps occur downstream of immediate chatter suppression. Scrap and rework should be measured directly, including the frequency of rejected parts, discarded material mass, corrective machining time, and the additional energy and tooling associated with recovery operations. Reliance on surface roughness or vibration reduction as proxies cannot establish whether material waste has actually been reduced.

The relationship between chatter and component durability also requires stronger causal validation. Existing studies indicate that chatter-related surface and subsurface degradation can influence fatigue behavior [13], but relatively few experiments trace the complete progression from machining instability through surface-integrity modification to measured service-life reduction. Future studies should therefore combine controlled chatter conditions with surface-integrity characterization, fatigue testing, and component-life assessment.

Environmental assessment should similarly expand beyond machining-stage electricity where sufficient data are available. Tool production and replacement, workpiece losses, scrap and rework, consumables, machine utilization, and component service life can all alter the overall environmental consequence of a chatter-management strategy. These effects should be quantified using clearly defined system boundaries and appropriately validated inputs rather than inferred from improved stability or productivity alone.

Ultimately, the central research challenge is no longer simply to demonstrate that intelligent methods can predict or suppress chatter. It is to establish, under realistic and transferable operating conditions, when, by how much, and through which mechanisms intelligent chatter management reduces resource consumption and environmental impact. Addressing this question would provide the evidence required to move the field from sustainability potential toward quantitatively demonstrated sustainable machining.

10.4. Technology-Specific Future Research Directions

Beyond the cross-cutting priorities discussed above, several research directions emerge for individual chatter-management technologies.

Monitoring: Future research should prioritize reliable identification of incipient chatter under variable cutting conditions, sensor noise, tool wear, and changing structural dynamics. Low-cost machine-internal sensing, adaptive signal processing, and multimodal sensor fusion require further evaluation in industrial environments, particularly regarding detection latency, sensor robustness, and false-alarm rates.

Machine learning: Greater emphasis should be placed on cross-machine and cross-material generalization, limited-data learning, class imbalance, and uncertainty-aware prediction. Transfer learning, domain adaptation, and continual learning should be evaluated using independent cutting trials and previously unseen operating conditions rather than random partitions of closely related signal samples.

Physics-informed approaches: Future developments should integrate regenerative dynamics, process damping, tool wear, and time-varying structural properties into hybrid learning models. Particular attention should be given to online parameter identification, uncertainty quantification, and physically consistent predictions outside the original training domain.

Adaptive control: Research should move toward predictive and safety-constrained control strategies that intervene before fully developed chatter occurs. Reinforcement learning and model-predictive control require stronger experimental validation, with explicit consideration of controller latency, stability guarantees, actuator limitations, and the energy and resource costs of intervention.

Digital twins: Future systems should incorporate continuous synchronization, online model updating, uncertainty estimation, and bidirectional integration with CNC controllers. Their effectiveness should be demonstrated through long-duration industrial applications and quantified improvements in stability, productivity, tool life, and resource consumption rather than architectural functionality alone.

Sustainability assessment: Future studies should quantify energy per acceptable component, tool consumption, scrap, rework, material losses, and carbon emissions under clearly defined system boundaries. Integration of life-cycle assessment with chatter monitoring and control should account for the additional energy and hardware requirements of intelligent systems. Controlled comparisons between conventional and intelligent strategies are needed to establish net sustainability benefits.

These directions emphasize the transition from isolated algorithmic or stability improvements toward transferable, physically credible, and experimentally validated intelligent machining systems with demonstrable sustainability outcomes.

10.5. Practical Implementation Recommendations

The industrial implementation of intelligent chatter-management systems should follow a staged approach that considers sensing feasibility, computational requirements, process variability, controller integration, and measurable manufacturing benefits. Initial deployment should prioritize accessible and robust monitoring signals, such as accelerometer measurements and machine-internal spindle-current or power signals, while additional sensors should be introduced only when their diagnostic contribution justifies the associated installation, calibration, and maintenance requirements.

Monitoring and prediction models should first be calibrated and validated under representative machining conditions, including variations in spindle speed, feed rate, depth of cut, tool wear, workpiece geometry, and material properties. Before closed-loop implementation, the systems should be evaluated for detection latency, false alarms, robustness to sensor noise, and performance under previously unseen operating conditions. Physics-based stability constraints and uncertainty estimates can improve reliability when applying data-driven models outside their initial calibration domain.

Control implementation should proceed progressively from advisory monitoring and operator-supported parameter adjustment toward supervised adaptive control and, where sufficiently validated,

autonomous intervention. Controller communication delays, actuator limitations, machine safety constraints, and fallback operating conditions should be explicitly considered. Digital-twin implementations should similarly prioritize reliable data exchange, computational efficiency, and periodic model updating rather than architectural complexity alone.

Finally, industrial performance should be assessed against a clearly defined conventional baseline using production-level indicators, including energy consumption per acceptable part, machining time, tool life, scrap and rework rates, and system downtime. The energy and maintenance requirements of sensors, computation, and control hardware should also be included when assessing net sustainability benefits. This staged implementation strategy can support reliable industrial adoption while ensuring that technological improvements translate into measurable manufacturing and environmental outcomes.

11. Conclusions

This review examined intelligent chatter management through five complementary research questions spanning physical mechanisms, technological evolution, deployment readiness, sustainability evidence, and remaining research needs.

First, chatter affects sustainability through multiple pathways, including reduced productivity, degraded surface quality, accelerated tool wear, additional energy demand, rework and scrap, and potential deterioration of component service life. However, the strength of evidence varies considerably across these pathways. Productivity and quality effects are well established, tool-related impacts are moderately supported, while direct evidence for energy, scrap, life-cycle, carbon, and LCA outcomes remains limited.

Second, chatter management has evolved from analytical stability prediction and offline stability-lobe selection toward sensor-based monitoring, machine learning, physics-informed intelligence, adaptive control, and digital twins. Third, the most deployment-ready approaches are those that combine physical consistency with online sensing and model updating. Purely data-driven systems remain constrained by transferability, changing process dynamics, and limited validation across machines, tools, materials, and geometries.

Fourth, the review reveals a clear mismatch between technology maturity and sustainability-evidence maturity. Advanced monitoring and control systems are commonly validated using detection accuracy, vibration reduction, stability, MRR, and surface-quality indicators, while direct resource and environmental metrics are reported far less frequently. The proposed SEL framework makes this imbalance explicit and should be interpreted together with whether reported benefits are measured, modelled, or scenario-assumed.

Future work should evaluate stable machining through energy use, tool consumption, scrap, productivity, component durability, and environmental impacts. The SEL framework provides a structure for this assessment, but conclusions about the distribution of evidence remain provisional until screening and study-level coding are complete.

Statement of the Use of Generative AI and AI-Assisted Technologies in the Writing Process

Generative AI tools (chatgpt) were used solely to support language editing, improve clarity, and refine the presentation of the manuscript. All scientific content, interpretations, references, and conclusions were reviewed and verified by the authors, who take full responsibility for the final manuscript.

Author Contributions

Conceptualization, M.Ç. and E.A.; Methodology, M.Ç.; Supervision, M.Ç.; Investigation, L.T.A. and M.M.B.; Writing—Original Draft Preparation, F.K.; Writing—Review & Editing, M.Ç., L.T.A., F.K., M.M.B. and E.A.

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