

Applied AI for Intelligent Die and Tooling Lifecycle Management in Aluminium Manufacturing

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Abstract- The manufacture of aluminium products by extrusion, die casting and related machining relies on tooling whose condition affects quality, scrap and production continuity. This narrative review examines how applied artificial intelligence can connect design, production, inspection and maintenance into an intelligent tooling lifecycle. It draws on 33 research publications dated 2020–2026, comprising the original 30-publication corpus and three publications added through a targeted update. Separate guidance from the Project Management Institute informs an adaptation of Cognitive Project Management for AI for decision governance. Aluminium-specific research supports selected design and quality-prediction tasks; adjacent machining studies demonstrate sensor-based and image-based wear estimation, remaining-life prediction and digital-twin monitoring. Transfer of these methods to extrusion and die-casting tools requires separate validation. Recent simulation-based extrusion-die optimisation strengthens the design evidence without establishing industrial die-life benefits. Key challenges include sparse damage labels, changing operating conditions, transfer between die families, uncertainty assessment and fragmented lifecycle records. A closed-loop framework links design, virtual qualification, production sensing, diagnosis, prognosis, maintenance and knowledge capture. The synthesis supports evaluation of human-supervised hybrid intelligence combining physical understanding with traceable data-driven predictions. Governance separates model release, intervention approval and return-to-service authority, with named owners, decision records and reapproval after material changes. The integrated framework remains a proposal; effects on die life, scrap, downtime and decision quality require prospective industrial evaluation.

Index Terms— artificial intelligence, aluminium manufacturing, dies and tooling, lifecycle management, decision governance

I. INTRODUCTION

Dies and production tooling are important assets in the manufacture of aluminium products since

deterioration in geometric features, thermal response, surface condition, or positioning may result in significant losses in both product quality and production efficiency. In the case of extrusion, the die determines the flow of the metal, the dimensions of the profile, the formation of the weld, the surface finish, and press stability. In high-pressure die casting, die geometry and thermal conditions influence filling, solidification, heat removal, dimensional repeatability and defect formation [1], [2]. Machining operations involving these tools also use additional cutting tools whose wear affects the quality of the die inserts, the repair surfaces, and the final aluminium components. In all these situations, the choices made regarding tooling have an impact on the amount of scrap, energy consumption, maintenance labour, delivery reliability, and the length of useful life obtained from costly assets. Factory digitalisation has increased interest in condition-based and predictive maintenance using machine learning and sensor data [3], [4]. Tool-condition monitoring provides relevant methods for machining operations [5].

The real problem is that the deterioration of dies and tooling cannot be described by a single measurable factor; instead, it results from the interaction of thermal, tribological and mechanical processes influenced by geometry and operating conditions. The dies used in extrusion are subjected to thermal cycling, adhesion, abrasion, oxidation, local deformation, bearing wear, and degradation of the coating. Die-casting tools on the other hand suffer repeated heating and cooling, erosion, soldering, thermal fatigue, cracking, and dimensional drift. Research on nitrided die steel and extrusion-tool wear shows how thermal exposure and local contact mechanisms contribute to degradation [6]–[8]. These findings inform life modelling but do not provide a universal die-life equation. Moreover, instrumented production systems can provide process histories that include temperature, pressure, load, vibration, acoustic

emission, power, images, cycle counts, inspection results, and quality outcomes.

Applied artificial intelligence (AI) offers techniques for learning complicated relationships between design variables, process conditions, signals, wear states, and quality results. There are already some studies that show the use of neural networks for quality prediction in aluminium die casting [9], the application of explainable machine learning to porthole extrusion-die design [10], and the use of deep learning for inspecting internal defects in aluminium castings [11]. Within machining, sensor fusion [12], hybrid physics-data monitoring [13], [14], remaining-useful-life prediction [15] and digital-twin monitoring [16], [17] provide complementary methods for estimating tool condition. This progress makes it possible to consider the die or tooling as an asset over its lifecycle rather than as a standalone consumable. Viewing it in this way connects the first design intent, the manufacturing history, the operating conditions, the predicted degradation, any maintenance actions taken, and the feedback received into the subsequent design cycle.

The selected literature addresses different parts of the problem: aluminium-specific work includes die design, tribology and product quality, while much of the condition-monitoring evidence examined here concerns machining cutters. A method which classifies cutter wear after each machining pass cannot be simply transferred to a large hot-work die without taking into account sensor accessibility, thermal inertia, maintenance practices, and the cost of false alarms. That is why this review seeks to address how applied AI can be organised throughout the entire tooling lifecycle, which evidence is directly relevant to aluminium manufacturing, which methods can be adapted for transfer, and what technical gaps currently hinder reliable industrial implementation.

The targeted 2026 update adds extrusion-die optimisation [18], an overview of high-pressure die-casting digitalisation [19], and a review of physics-data integration for machining wear prediction [20]. These extend the design and integration context without resolving the need for prospective die-lifecycle validation.

The goal is to create a consistent review framework for the management of the lifecycle of intelligent dies and tooling in the aluminium manufacturing industry. The synthesis is guided by four objectives: first, to identify the failure mechanisms throughout the lifecycle and the data that they produce; second, to compare the various AI methods available for use in design support, condition monitoring, prognosis, and making maintenance decisions; third, to assess the role of hybrid physics-AI and digital-twin architectures; and fourth, to suggest an implementation framework that connects traceability, uncertainty and human supervision through structured decision governance. This approach goes beyond simply comparing algorithms to address a decision-focused question: how can AI help manufacturers obtain more reliable value from each die while preserving quality, safety and engineering account-ability?

This governance extension adapts the Cognitive Project Management for AI (CPMAI) methodology of the Project Management Institute (PMI), which also offers the PMI Certified Professional in Managing AI (PMI-CPMAI) credential. The official methodology overview describes an iterative lifecycle linking business purpose, data, model development, evaluation and operational use [21]. For tooling, the design problem is to specify which evidence permits a recommendation to inform production, inspection, repair or retirement, and who remains accountable. A model cleared for condition estimation does not thereby clear an individual die for continued service. The proposed adaptation makes this distinction explicit without claiming demonstrated improvements in tooling performance.

II. REVIEW DESIGN AND ANALYTICAL METHOD

This paper is a narrative review of 33 research publications dated 2020–2026: the original 30 publications from 2020–2025 and three 2026 publications incorporated during a targeted update completed on 4 October 2026 [18]–[20]. Its scope covers five related topics: aluminium die and extrusion-tool behaviour; AI-enabled manufacturing quality prediction; tool-condition monitoring; remaining-useful-life and predictive-maintenance modelling; and digital-twin or physics-informed

decision support. Publication years follow the cited journal volume or proceedings, rather than the year embedded in a DOI; the Chen et al. article was first published online in January 2026 [18]. The review develops an engineering synthesis and a proposed framework; it does not claim an exhaustive search, a reproducible systematic selection process or a quantitative meta-analysis.

The original 30-publication corpus is retained as a selected narrative evidence base. The available review record does not document its original databases, search dates, complete queries, retrieval totals or exclusion decisions; these cannot be reconstructed reliably from the bibliography. For this revision, a targeted web search and direct publisher/DOI checks examined recent work using title queries and themes including aluminium extrusion-die optimisation, smart manufacturing in high-pressure die casting, and physics–data integration for tool-wear prediction. The three 2026 papers identified in the manuscript review were checked on Springer Nature, ScienceDirect and the authors’ institutional repository where available, and retained because they directly address design support, casting digitalisation or hybrid tool monitoring. These checks update selected themes through 4 October 2026 but do not establish complete coverage of 2026 literature. Full text was consulted for the new extrusion-die study and high-pressure die-casting overview; discussion of the new machining review is limited to its publisher abstract and bibliographic record. Adjacent machining studies are retained for transfer-able monitoring and prognosis methods, with their findings distinguished from direct evidence about aluminium dies. This selection remains vulnerable to selection bias and does not support estimates of research prevalence.

Two official PMI sources, consulted on 4 October 2026, provide professional methodology guidance [21], [22]. The principal source is the CPMAI Methodology Overview [21], supported by PMI’s explanation of the six phases [22]. These sources are additional to the 33 research publications and are not industrial validation evidence. The six CPMAI phases are mapped to tooling decisions; required evidence, accountable roles and escalation rules are specified through engineering reasoning. This interpretive

adaptation has not been assessed through stakeholder interviews or plant trials.

The cited literature includes background reviews [3]–[5], [19], [20], empirical investigations, modelling studies and conference contributions. Each review is counted once as a publication; its constituent studies are not added to this corpus or treated as independent experimental validations of the proposed framework. Aluminium-specific research is considered alongside adjacent machining research because the latter supplies relevant monitoring and prognosis methods. Their transfer to extrusion and die-casting tools is assessed as an engineering possibility requiring separate validation. Table I maps the proposed lifecycle decisions to candidate data and AI methods; Table II summarises selected source findings and the limitations of transferring them to dies.

The discussion is organised around four analytical dimensions. The first of these concerns the lifecycle stage, which includes the design and virtual qualification phase, the manufacture and commissioning of tools, production operations, condition monitoring, life prognosis, maintenance or repair, and knowledge feedback. The second dimension is the type of data, and this comprises geometry and simulation fields, scalar process parameters, time-series signals, images, maintenance records, or combinations of these. The third dimension refers to the function of the AI, and this involves prediction, classification, anomaly detection, optimisation, remaining-life estimation, explainability, or decision support. The fourth dimension is related to the level of deployment maturity, and this includes offline model development, near-real-time monitoring, the use of a digital shadow, a synchronised digital twin, or closed-loop decision assistance.

The critical discussion asks four questions: whether a model is consistent with known degradation behaviour; whether its validation covers relevant process variation; whether uncertainty and limitations are reported; and whether its output can support an engineering action. These questions guide a qualitative interpretation rather than a formal study-quality score. Reported outcomes are considered within each study’s material, tool, task and validation conditions; accuracy

values from different datasets are not treated as directly comparable. The proposed framework is a synthesis of this evidence and engineering reasoning, not a tested end-to-end implementation. The selected corpus and narrative approach limit conclusions about the prevalence or superiority of particular methods across the wider literature.

III. ALUMINIUM TOOLING FAILURE MECHANISMS AND LIFECYCLE DATA

Intelligent lifecycle management begins by defining in physical terms what is deteriorating. Aluminium extrusion serves as a straightforward example. The die works under high pressure and temperature. In port-hole extrusion, aluminium flows through ports, around bridges and mandrels, into welding chambers and through bearing regions. Annealing experiments on nitrided WNLV steel identify surface changes associated with thermal exposure [6]. Laboratory and industrial studies of extrusion-tool materials identify wear mechanisms including adhesion, abrasion, oxidation, cracking and material detachment [7], [8]. The relevance of each mechanism depends on the material, surface treatment and contact conditions. Such damage can alter bearing geometry and friction, with consequences for flow balance, dimensional tolerance and surface quality. Degradation is thus spatial in character: different areas of the same die can accumulate damage at different rates. Therefore, a lifecycle model must take into account both location and time.

The tooling used in die-casting also has to deal with a problem that is related but at the same time distinct. Each cycle combines high-speed molten-metal flow, rapid heat transfer and subsequent cooling. The repeated occurrence of thermal differentials leads to fatigue and cracking, while local flow can cause erosion or soldering. The state of the tool then interacts with the injection velocity, the die temperature, the temperature of the aluminium at the inlet, the cooling arrangement, and the method of releasing the product. Historical die-casting data have been used for product-quality prediction with a shallow neural network and feature selection [9]. Torres et al. report preliminary laboratory digital-twin development combining sensing, simulation and AI for process monitoring and prediction; predictive maintenance and testing across

other geometries and alloys are identified as future work [1]. Deep learning has also been used to detect and classify defects in radiographic images of aluminium castings [11]. Linking these defect patterns to die condition is a proposed extension: it would require independent measurements of die damage and control of other causes of casting defects.

The evidence that is relevant may consist of the cycle count, local or global temperatures, hydraulic or injection pressure, the press load, the billet or melt temperature, lubrication or release settings, the cooling flow, the spindle or motor current during the making of the tool, vibration and acoustic emission, dimensional inspection, surface images, the repair history, the coating or nitriding history, and the product-quality results. Research into tool conditions shows that force, vibration, sound, current, temperature, and image data each pick up different aspects of degradation [5], [12], [23]–[25]. Multi-sensor studies illustrate how complementary measurements can support condition estimation [12], [25]. For die applications, any benefit must be weighed against sensor cost, synchronisation requirements and data-governance workload; adding sensors does not automatically improve prediction.

The way in which degradation progresses is just as significant. Although wear generally develops slowly, incidents like local chipping, the initiation of cracks, blocked cooling, abnormal lubrication, or a disruption in the process may cause a sudden change in the pattern. Remaining-life predictions must therefore make a distinction between accumulated damage and sudden anomalies. Temperature-based wear prediction [23], time–frequency-based life prediction [15] and physics-informed state modelling [26] provide different ways to represent tool degradation. Their respective results do not establish that temporal models are universally more robust than static classifiers. In the case of aluminium dies, a similar approach would entail modelling the cumulative thermal cycles, the local stress exposure, the contact conditions, and the observed quality drift while at the same time allowing discrete maintenance events to alter the degradation state without assuming complete renewal.

Lifecycle models also need to account for maintenance history. If a die is repaired, re-nitrided, re-polished, welded, modified, or reassigned to a different product, the asset should not be assumed to return to an as-new state; retained damage and changed geometry may affect subsequent performance. An AI system that is to be useful therefore has to keep a record at the level of each asset, linking the first design and materials to all the manufacturing, production, inspection, and

maintenance events. This is more demanding than simple process monitor-ing since the prediction depends on the die's complete history. As a result, the lifecycle approach regards data architecture as belonging to the engineering methodology rather than treating it as an after-the-fact information-technology concern.

TABLE I
PROPOSED MAPPING OF ALUMINIUM DIE AND TOOLING LIFECYCLE DECISIONS TO DATA AND AI METHODS.

Lifecycle stage	Dominant engineering question	Representative data	Candidate AI contribution	Primary deployment risk
Design / virtual qualification	Will the geometry provide balanced flow, strength and ease of manufacture?	Computer-aided design (CAD) geometry, simulation fields, prior successful designs	Surrogate modelling, optimisation, explainable prediction	Historical-design bias and extrapolation outside known geometries
Manufacture / commissioning	Does the as-built tool match design intent and baseline condition?	Metrology, hardness, coating/nitriding records, trial data	Anomaly detection, baseline clustering, image inspection	Incomplete as-built records and inconsistent inspection
Production operation	Are process conditions stable and within validated limits?	Temperature, pressure/load, speed, current, cycle history	Quality prediction, adaptive thresholds, multivariate monitoring	Confounding between process change and true tooling degradation
Condition monitoring	What damage state is developing and where?	Vibration, acoustic emission, thermal data, images, dimensional checks	Sensor fusion, classification, wear estimation, computer vision	Sparse labels, inaccessible damage and sensor drift
Life prognosis	How much reliable service remains under current conditions?	Health indicators, degradation history, process severity, maintenance history	Remaining-useful-life estimation, probabilistic prognosis, physics-informed learning	Overconfident point predictions and changing operating regimes
Maintenance / repair	Continue, inspect, repair, recondition or replace?	Predicted risk, repair lead time, spare availability, quality consequence	Decision support, cost-risk optimisation, prescriptive analytics	Automation bias and thresholds that ignore consequence
Knowledge feedback	What should change in the next design or process plan?	Failure maps, maintenance outcomes, design revisions, quality history	Knowledge mining, explainable pattern discovery, controlled learning	Poor asset identity, missing lineage and ungoverned model updates

IV. THE APPLICATION OF AI THROUGHOUT THE TOOLING LIFECYCLE

The way in which AI contributes varies at each stage of the lifecycle. In the design phase, the main goal is to turn historical experience into quicker and more consistent engineering decisions. Llorca-Schenk et al. apply explainable machine learning to geometric data from 596 ports in 88 successful first-trial porthole dies [10]. Their work supports a specific port-design task within a defined die typology, rather than general optimisation of all extrusion-die geometries. This is important since die design is knowledge intensive and usually involves repeated simulation-correction cycles. Within a validated design domain, a model may suggest starting dimensions or identify influential geometric variables. Extension to other die families requires new validation, and physical verification remains necessary through appropriate simulation and trials. In this capacity, AI functions as design support and a means of reusing knowledge rather than taking the place of engineering analysis. Chen et al. extend this design evidence through a 2026 framework that combines surrogate models, active sampling and optimisation for aluminium extrusion dies [18]. Their T-bar case uses finite-element-generated data and evaluates flow uniformity against simulation. It supports simulation-assisted geometry search within the investigated parameterisation; physical production trials, other profile families and die-life outcomes require separate validation. The optimisation objective is flow behaviour, not demonstrated improvement in tool durability.

During commissioning and production, artificial intelligence has the ability to discover the relationships between the process settings and the quality. In the case of aluminium die casting, shallow neural networks together with feature selection have been applied in order to predict the quality of the product and to identify variables associated with the predicted outcome [9]. A related approach could be evaluated in extrusion trials: the dimensions of the profile, the press load, the exit temperature, the flow balance, and the surface observations could provide inputs for models intended to reduce correction loops. Whether they achieve that reduction would need to be tested. The key requirement here is to distinguish between

correlation and causation; a model might find a variable to be predictive simply because it varies with some underlying factor. It is therefore necessary to have explainability, controlled validation, and to take into account the physical constraints before using the predictions to alter the die geometry or the operating limits.

The 2026 overview by Lehmhus et al. examines data acquisition, management and AI-supported evaluation in high-pressure die casting [19]. It reinforces the importance of connecting process information to quality and control decisions, while providing contextual synthesis rather than independent validation of a complete die-health lifecycle.

Condition monitoring provides several examples of potentially transferable methods. Studies using sensor fusion have estimated tool wear and surface roughness from vibration and acoustic signals [12], and temperature-based deep learning has demonstrated that thermal data can monitor progressive wear [23]. By combining acoustic-emission features with machine learning it is possible to identify different tool-condition classes [24]. Hybrid methods that combine data-driven and model-informed approaches reduced false alarms in the reported milling experiments by comparing measured signals with predictions of nominal behaviour [13], and information theory-based methods can be used to select the most useful combinations of sensors and operating tests [14]. These studies indicate a practical way of proceeding for dies: instead of installing sensors for every possible variable, manufacturers should choose sensors that are both physically connected to the main damage mechanisms and provide information relevant to the decisions that need to be made.

There is another approach based on images. The amount of tool wear that occurs when machining AA7075 has been estimated by means of image processing and machine learning, showing how direct visual evidence can supplement process data [27]. The use of deep learning to detect defects in aluminium castings includes evaluation on the AI-Cast dataset of 3,466 images [11]. This demonstrates a casting-inspection application, not direct diagnosis of die degradation. With regard to tooling management,

similar visual models could examine the die-bearing surfaces, cracks, soldering, erosion, coating damage, or the quality of repairs from images obtained during controlled inspections. A benefit is the availability of visual evidence for engineering inspection, although this does not make the model's reasoning automatically interpretable. The drawback is that many critical die failures start below the visible surface or in areas that are not accessible, so visual models should be combined with thermal and process signals rather than be considered as full health assessments.

Prognosis adds a time horizon to condition assessment. Remaining-useful-life (RUL) models estimate how long a tool can continue to be used before a specific limit is reached. Use of time-frequency features together with recurrent and convolutional networks has led to useful estimates of milling tool life [15]. Digital-twin studies include spindle-current-based micro-tool wear estimation [28] and tool models in-tegrating simulation, data fusion and machine learning [16], [17]. AI-assisted digital shadows are capable of providing wear estimates with low latency at the machine edge [29], and ensemble digital-twin monitoring has demonstrated online predictions under the investigated milling conditions [17]. The latter study identifies variable-condition validation as further work. In the case of aluminium dies, the remaining life should not be given as a single deterministic value. A more defensible output would be a probability distribution or a risk band associated with a particular failure mode, product family, and operating regime.

Recent machining studies illustrate the importance of physics-informed and explainable learning. Through incorporating known wear progression into the state structure, physics-informed hidden-state models aim to improve wear monitoring across the investigated machining conditions [26]. Gaussian-process and machine-learning methods that are physics-informed combine data with wear mechanisms to encourage consistency with the physical assumptions used in the model [30], [31]. Semi-supervised learning can make use of the unlabelled production data while at the same time restricting the pseudo-labels using wear laws [32], a situation that is especially pertinent to dies since genuine end-of-life labels are rare and costly.

Multi-modal explainable AI identifies how image and time-series features contribute to tool-condition classification [33]. Such explanations support inspection of model behaviour but do not themselves establish user trust or physical causation. Taken together, these studies make hybrid modelling a promising candidate for die lifecycle management; they do not establish its superiority in a complete industrial die lifecycle.

V. AN INTEGRATED AI FRAMEWORK FOR THE INTELLIGENT MANAGEMENT OF THE DIE AND TOOLING LIFECYCLE

Fig. 1 presents the proposed lifecycle as a closed loop. It is a conceptual framework, not an experimentally validated control system. The nine physical lifecycle stages and the five technical layers in Fig. 2 serve different purposes from CPMAI: its six phases govern development, release and re-vision of each AI use case across the asset lifecycle. The requirements and die design determine the geometry, the material, the expected loads, the allowable deflection, the thermal limits, the surface treatment, and the quality targets. Virtual qualification then assesses the risks relating to filling, flow, stress, temperature, deformation, and fatigue. AI could assist these tasks through reuse of successful designs or surrogate models of selected simulation outputs. Any computational advantage and prediction error must be assessed against the underlying simulation and engineering constraints. After the tool has been manufactured and put into operation, its as-built dimensions, hardness, coating or nitriding condition, and the results of the trials become the baseline state for future comparisons.

While the system is in operation, a particular set of sensors produces a condition signature, the right combination being determined by the main failure mechanisms and the economic considerations of the plant. If thermal fatigue and cooling imbalance are the dominant factors, then temperature is key; load and pressure can reveal changes in flow or friction; vibration and acoustic emission are candidate indicators of cracking or unstable contact, subject to validation in the particular die installation; machine current can act as a cheap indicator of mechanical demand; and periodic images or metrology can directly measure any change in surface condition or

dimensions. The data should be synchronised by cycle or production batch in order that each health estimate can be associated with the actual process conditions, the product quality, and the identity of the die.

Fig. 2 divides the system into five decision layers. The data layer is responsible for obtaining information from a number of sources and carries out time

alignment, validation, and contextual tagging. The context-and-physics layer transforms the raw data into engineering variables through incorporating geometry, material properties, operating conditions, known wear mechanisms, and simulation outputs. In the intelligence layer, candidate models include tree-based methods

TABLE II
SELECTED STUDY FINDINGS AND THEIR IMPLICATIONS FOR THE PROPOSED TOOLING LIFECYCLE.
TRANSFER LIMITATIONS ARE THE INTERPRETATION OF THIS REVIEW.

Study	Manufacturing context	AI / digital method	Reported contribution	Implication for transfer to dies
Bak et al. [9]	Aluminium die casting	Feature selection + shallow neural network	Links process conditions to predicted product quality	Quality correlation does not directly identify die damage
Hubicki et al. [6]	Nitrided WNLV die steel	Annealing and surface analysis	Relates thermal exposure to surface changes	Not a direct lifetime test or online AI model
Zhao et al. [7]	Hot-extrusion die materials	Experimental + numerical wear analysis	Provides mechanism-level evidence for wear-aware models	Requires adaptation to individual industrial die geometries
Llorca-Schenk et al. [10]	Porthole aluminium extrusion dies	Explainable machine learning	Reuses successful design knowledge and explains influential geometry	Validated within a defined die typology
Chen et al. [18]	T-bar aluminium extrusion die	Surrogate models + optimisation	Simulation-based improvement of flow behaviour	No physical production or die-life validation
Yang et al. [13]	Milling tool monitoring	Hybrid physics-data anomaly detection	Reduced false alarms in reported milling experiments	Machining signals are more accessible than die damage
Awasthi et al. [14]	Precision machining	Physics-based modelling and sensor selection	Supports informative sensor and test-condition selection	Model parameterisation can be demanding
Sayyad et al. [15]	Milling tool life	Time-frequency features + deep learning	Demonstrates remaining-life prognosis from degradation signals	Machining data do not establish die-life performance
Zi et al. [17]	Milling cutter	Digital twin + ensemble learning	Near-real-time wear state and value monitoring	Variable-condition performance needs further testing
Chehrehzad et al. [29]	Drilling tools	AI-assisted digital shadow at edge	Online drilling-wear estimation at the machine edge	Transfer depends on suitable die-level proxies
Pashmforoush et al. [30]	Turning tools	Physics-informed machine learning	Combines mechanistic wear/force behaviour with learning	Requires credible physical submodels
Niu et al. [32]	Machining tool	Semi-supervised	Uses unlabelled data while	Pseudo-label quality

	wear	learning constrained by wear laws	respecting progression	remains model dependent
Sotubadi et al. [33]	Machining tool wear	Multi-modal explainable neural network	Explains image and time-series contributions to classification	Explanations describe model behaviour, not causation
Lehmhus et al. [19]	High-pressure die casting	Overview of digitalisation and AI	Connects data acquisition, management and process evaluation	Contextual review; not die-life validation
Tavares and Hassui [20]	Turning and milling	Review of physics–data integration	Identifies reporting and validation gaps across 122 studies	Abstract-level use here; underlying studies not pooled

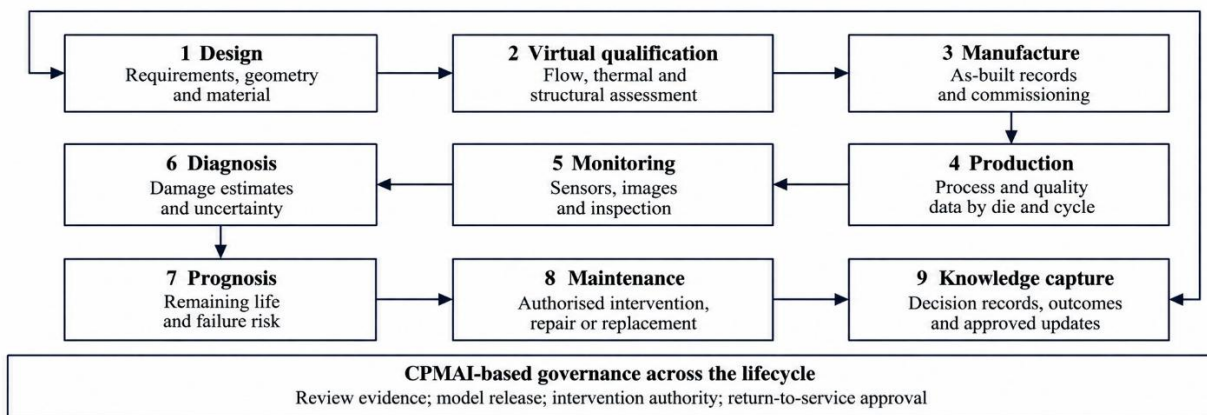


Fig. 1. Proposed closed-loop asset lifecycle with CPMAI-based decision governance across all stages. The nine asset stages are distinct from the six CPMAI phases. Arrows show intended information and decision flow; no measured performance or automatic control capability is implied.

for structured data, support-vector methods, convolutional or recurrent networks for images and time series, ensembles, and physics-informed methods. Selection should depend on the task, sample size, baseline comparisons and validation under the intended operating conditions. Neither an ensemble nor a physical constraint guarantees robustness or reliable extrapolation. Explainability is not an independent reporting feature; it is included within the intelligence layer since the evidence justifying a recommendation must be visible before any action is taken.

The decision module converts the predictions into concrete actions such as continuing production, inspecting at the next scheduled stop, altering the process settings, carrying out a repair, reconditioning the die, re-nitriding it, or replacing the tool. When optimising maintenance, both the consequences and

the predicted wear should be taken into account. A die that is only moderately degraded and which is producing a critical dimensional feature might warrant earlier intervention than one that is more worn and producing a tolerant profile. Similarly, the decision threshold must take into consideration the batch size, the availability of spare dies, the repair lead time, the risk of catastrophic damage, the expected cost of scrap, and the downstream delivery obligations. In this way, AI supports operational decisions as well as wear estimation.

The fifth level concerns governance and value, with CPMAI-based lifecycle review spanning all five layers. Section VI distinguishes model release, intervention approval and return-to-service authority. Each prediction must include the version of the model, the quality status of the input data, a measure of confidence or uncertainty, and a traceable reference to

the history of the underlying asset. Human approval should be obtained before any changes to the geometry, when making major maintenance decisions, and when inputs fall outside validated conditions. In the latter case, model recommendations should be withheld or treated as unvalidated pending engineering review. Performance should be assessed using engineering and business criteria such as prediction error, false-alarm rate, missed-failure rate, tool-life utilisation, scrap reduction, unplanned downtime, repair cost, energy intensity, and first-pass yield.

The framework also includes controlled model updating as new evidence becomes available. Following maintenance, the actual defect, the wear map, the location of any crack, the amount of material that was removed, the condition of the coating, and the restored shape should all be recorded. Subsequent production runs can help assess whether the intervention achieved the intended result, while accounting for changes in alloy, product and process settings. Comparing outcomes alone does not establish a causal maintenance effect. This feedback can produce labelled, asset-linked evidence for model development. Updated models should be versioned, revalidated and authorised before deployment. Repaired or modified tools also require their own engineering release; model reapproval does not replace this asset-specific decision. Over time, manufacturers could establish a die genealogy: a record of designs that needed fewer corrections, of conditions associated with faster wear, of maintenance actions associated with longer die life, and of failure signatures that occurred before a loss in quality. This kind of knowledge base could support predictive maintenance, future die design, process planning and supplier qualification.

VI. PMI-CPMAI-BASED GOVERNANCE AND IMPLEMENTATION

A. Lifecycle Reviews and Accountable Roles

PMI's six iterative CPMAI phases are listed in Table III; earlier phases may be revisited when evidence changes [21]. PMI also places business alignment, ethical oversight and governance throughout the lifecycle, including monitoring and operational accountability [21], [22]. The proposed tooling

adaptation uses review checkpoints to record whether to proceed, revise, hold or stop an iteration. The evidence requirements and role assignments below are this paper's engineering design, not mandatory PMI tooling procedures or a certification claim.

The plant sponsor approves the business case and resources. A named tooling engineering owner is accountable for the technical scope, degradation assumptions and permitted use of the AI service. The data owner accepts data-quality exceptions, the analytics lead develops and documents the candidate, and a reviewer separate from development checks validation evidence where practicable. Quality retains authority over product acceptance; production and maintenance execute only within their delegated procedures. The AI project manager coordinates evidence, approvals and change records without replacing these engineering responsibilities. Each plant should identify the actual role holders and resolve overlapping responsibilities before live use.

B. Model Release, Intervention and Return to Service

Three authorisations should be distinguished. Model re-lease permits a specified model-policy version to support a defined die family, failure mode and operating regime. Intervention approval selects an action for an identified asset using its current condition, uncertainty, product requirements and production context. Return-to-service approval confirms that a repaired, reconditioned or modified tool meets the plant's applicable inspection and qualification requirements. A favourable remaining-life estimate is supporting evidence for a decision, not permission to bypass inspection, extend an established operating limit or release a tool after repair.

The initial operating mode should be advisory: engineers review recommendations before changing die geometry, process limits, maintenance plans or retirement status. Routine administrative steps, such as creating an inspection task or routing an alert, may later be automated within explicit authority. Consequential choices, including welding, re-nitriding, geometry correction, extending service beyond an approved limit or withdrawing a tool from service, require the designated engineering and, where relevant, quality decision. Existing protective stops and established emergency procedures remain in

force. Numeric risk thresholds and review periods should be set from the plant's requirements and validation evidence, not inferred from a reported classifier accuracy.

For example, a prognosis may indicate elevated risk before the next planned stop. The decision package should identify the affected die region, supporting measurements, uncertainty,

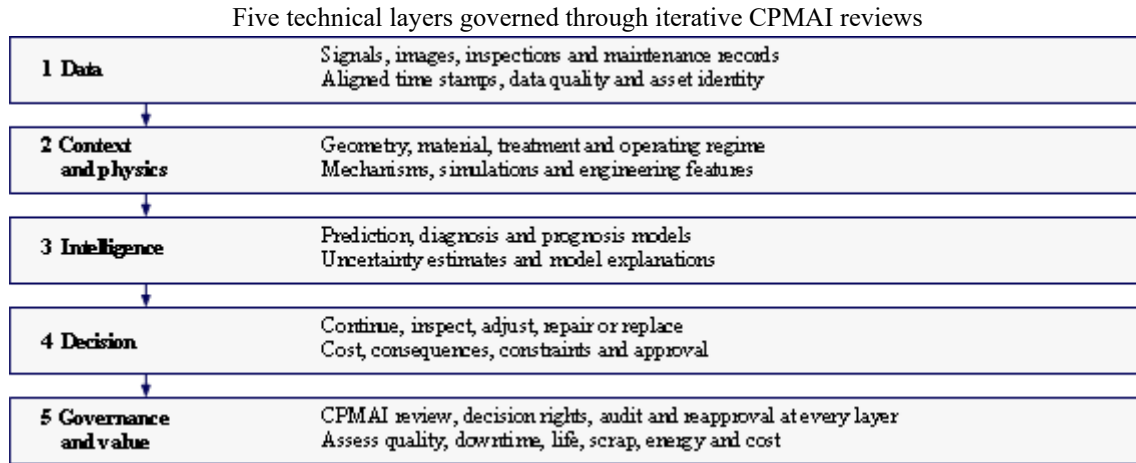


Fig. 2. Proposed five-layer architecture with CPMAl-based governance spanning all layers. Lifecycle review authorises a defined AI use case; engineering procedures authorise individual tooling actions. Performance measures are evaluation targets, not achieved results.

TABLE III PROPOSED TOOLING-GOVERNANCE CHECKPOINTS MAPPED TO THE CPMAl LIFECYCLE

CPMAI phase	Proposed review decision	Required tooling evidence	Proposed accountable owner
1. Business understanding	Is the AI use case justified, and which tooling decisions may it support?	Die family and failure mode; current inspection/maintenance baseline; quality and downtime objectives; consequences of missed damage; prohibited actions; acceptance criteria.	Plant sponsor, with tooling engineering and quality.
2. Data understanding	Can the available history distinguish tool damage from process variation?	Asset and insert identity; geometry/treatment revisions; sensor locations; alloy and process regimes; inspection labels; repair history; censored end-of-life records.	Data owner, with the tooling engineer.
3. Data preparation	Are health labels and decision-time inputs traceable and fit for testing?	Cycle alignment; units and calibration; inspected damage labels; maintenance-state changes; lineage; held-out tool/campaign splits; leakage and missing-data checks.	Data owner, supported by data engineering and inspection specialists.
4. Model development	Is the model consistent with the target mechanism and decision?	Baseline and candidate versions; physical assumptions; feature rationale; uncertainty output; limits for unfamiliar dies; reproducible model and threshold configuration.	Analytics lead for evaluation submission, without tooling-release authority.
5. Model evaluation	Does the complete recommendation	Held-out die and regime tests; missed-damage and false-alarm results; interval	Tooling engineering owner, with validation and quality review.

CPMAI phase	Proposed review decision	Required tooling evidence	Proposed accountable owner
	workflow meet agreed criteria?	calibration; explanation review; shadow trials; decision-cost and quality assessment.	
6. Model operationalization	Can the approved use case operate within a monitored scope?	Authorised die population; named approvers; action limits; versioned deployment; audit links; escalation and fallback tests; review cadence; change and retirement rules.	Tooling/process owner, with production, maintenance and system owners.

Source: Author's tooling-specific adaptation of PMI's CPMAI Methodology Overview [21], supported by [22].
Approval roles and evidence requirements are proposed controls requiring plant validation.

applicable operating regime and feasible inspection or re-placement options. The responsible engineer checks the evidence against inspection history and current constraints; an unexplained disagreement, sensor fault or unsupported regime should trigger escalation and the approved inspection/fallback procedure. After a repair, metrology and relevant inspection or trial results are attached to the new asset-state record before authorised return to service. Neither the repair event nor an updated prediction should automatically reset the die to an as-new condition. This sequence is a proposed control workflow rather than a demonstrated industrial result.

C. Traceable Decisions and Controlled Change

Each decision record should connect the die and insert identifiers, geometry revision, material and treatment, operating campaign, input snapshot and quality flags to the model and policy versions. It should preserve the predicted damage or RUL range, uncertainty, recommended alternatives, triggered authority rule, approver, override rationale and executed action. Post-intervention inspection, removed material, coating changes, dimensional results and subsequent quality outcomes should remain linked to the same genealogy. Recommendation, approval, maintenance completion and release are separate events; their timestamps and authors allow later review of what evidence was available when the decision was made.

Monitoring should examine prediction quality and the decision process, including missed damage, false alarms, data freshness, out-of-scope inputs, override patterns, approval delay and tool-related scrap or downtime. A failed control should suspend affected

automatic functions and route the case to the responsible owner. Changes in alloy, die geometry, treatment, sensor configuration, repair method or operating limits should trigger review of applicability and, when material, a return to the relevant CPMAI phases. New models and thresholds require documented validation and release approval; unreviewed online updates should not alter action authority. Restoring a previous model cannot undo a physical repair or consumed die life, so fallback must use the current asset state and established engineering procedures.

D. Staged Pilot and Governance Evaluation

A pilot should begin with one defined die family, failure mechanism and decision, an agreed baseline and named owners. Initial data work should establish reliable genealogy and inspection labels. Candidate models should then be evaluated retrospectively on separated tools and campaigns, followed by shadow operation in which recommendations are logged without changing production decisions. Advisory live use follows only when the evaluation review accepts the evidence and residual risks. Expansion to another die family, site or operating regime requires a new applicability decision; it is not implied by completing a pilot elsewhere.

The governance contribution should be evaluated separately from model accuracy. A prospective comparison could assess existing engineering practice, AI assistance under existing approvals, and the same AI assistance with the proposed review and decision-record controls, while retaining mandatory safeguards in every group. Alongside die-life utilisation, quality, scrap, downtime and maintenance cost, the

assessment should track traceability completeness, unauthorised-action attempts, override reasons, review effort and decision latency. Holding model and data preparation constant where feasible would help separate governance effects from technical improvements. No improvement is assumed in advance.

VII. CRITICAL ASSESSMENT AND SYNTHESIS OF THE EVIDENCE

The selected studies demonstrate the feasibility of individual functions, while evidence for their integration across complete die lifecycles remains limited. There are, on the one hand, offline models which measure quality or wear by using selected data; on the other hand, there are digital-twin and digital-shadow systems which receive live signals and give condition estimates with a near-real-time response. The shift between these different approaches is not simply a matter of introducing connectivity; it also requires having a persistent asset identity, updating the models, using reliable sensors, controlling latency, managing uncertainty, and making sure that there is a decision process which plant personnel can verify. The studies report classification or regression results for their respective machining tasks [17], [25], [26], [29]–[32], [34]. These results cannot be ranked directly because the datasets, targets and validation conditions differ. Die applications may involve different time scales, thermal exposure, operating variation and repair histories. This raises the risk of model drift and means that simple assumptions that wear follows a single monotonic curve from new to failure can no longer be held.

Hybrid modelling offers a useful basis for further investigation. Although physical models can expose mechanistic assumptions and support predictions outside observed data when those assumptions remain valid, they may have to incorporate parameters that are difficult to measure and which can be very computationally expensive. In contrast, completely data-driven models can quickly learn nonlinear patterns, but they are vulnerable to changes in the alloy, geometry, sensor placement, product mix, or maintenance procedures. Hybrid approaches seek to combine these advantages by making use of physical expectations to define the features, to constrain the

state changes, to generate the residuals, or to regularise the learning process [13], [14], [26], [30]–[32]. This is notably useful in the context of die lifecycle management since, even if the exact rate is uncertain, the failure mechanisms are well understood in a qualitative manner. The known relationships between temperature, contact, cyclic loading, and wear can therefore be used to guide the model without it being necessary to derive a fully deterministic life equation. Tavares and Hassui's 2026 review synthesises 122 machining studies published during 2020–2025 and distinguishes different ways of integrating physics and data [20]. Its abstract highlights inconsistent reporting of targets, sensing, validation and deployment assumptions. This strengthens the case for explicit evidence boundaries and comparable validation protocols; its underlying studies are not added to this review's corpus, and its machining findings do not establish industrial die-life benefits.

Data scarcity also constrains lifecycle modelling. A large number of recorded production cycles does not necessarily provide many independent die-life histories. Failure labels may also be incomplete because tools are retired preventively, repaired or reassigned before failure. Cycle-level observations should therefore not be treated as independent run-to-failure examples. One way of addressing this is through semi-supervised learning, which makes use of the vast amount of unlabelled data [32]. Alternative approaches include transfer learning and representation learning, but in order to use them safely it is necessary to have evidence that the source and target processes have some meaningful common structure. Synthetic data generated by a validated simulation can also improve coverage of rare conditions, but the errors from the simulation must be included in the uncertainty estimates. The aim should not be to create a false sense of certainty; rather it should be to make better use of the limited evidence and at the same time clearly indicate where the model is making extrapolations.

Explainability can support engineering review of model outputs. In the field of design, explanations about features enable engineers to see why a particular geometry is expected to perform well [10]. In machining, explanations of a multi-modal model identify contributions from tool images and recorded

process signals [33]. Applied to die monitoring, a similar approach could assist troubleshooting, but distinguishing die damage from sensor faults or production changes would require independent checks. It is important, though, to handle explanations with care. A feature-importance score illustrates how the model is behaving, but does not necessarily indicate physical causation. The most guarded approach is to compare the explanations with existing engineering knowledge and treat any disagreement as a reason to investigate.

The choice of prediction target is equally important. Wear is a measurable target in the machining studies considered here, but practical decisions also depend on product quality, production stability and risk. Defect classification itself can contain ambiguity and labelling error, which must be considered when using quality as a target [2]. A lifecycle system should therefore incorporate a number of interconnected targets: the actual level of deterioration or damage, the probability of producing defective parts, the probability of failure before the next scheduled stoppage, and the economic impact of carrying out an intervention. Multi-objective optimisation has been investigated for surface roughness and cutting-tool wear in AA6061 milling [35]. Extending such optimisation to maintenance timing would require models of intervention cost and failure consequences. The timing of replacement should consider expected risk and cost within approved engineering and quality constraints. Economic optimisation does not justify continuing beyond an applicable damage limit or overriding a required inspection or withdrawal decision.

The significance of temperature history is also shown by evidence specific to aluminium. Annealing experiments on nitrided WNLV steel show surface changes relevant to thermal degradation [6], and investigations into wear at high temperatures indicate that the damage mechanisms vary with the amount of exposure and the sliding history [7], [8]. These findings suggest that cycle count alone may be insufficient to characterise die condition. Two dies which have the same cycle count could have different degradation states if one of them had a higher billet temperature, longer dwell times, inadequate cooling, or a more aggressive profile geometry. An AI model

can combine these histories only if the process data are reliably linked to the correct die and if missing data are dealt with explicitly.

The business case depends on how the system is deployed. Signals that are cheap to obtain, such as motor current or conventional machine data, may in some cases offer useful indications of wear [28], [34], while multi-sensor studies illustrate complementary measurement strategies [12], [25]. The cost–accuracy trade-off must be established for the intended installation. Spindle-power monitoring in drilling carbon-fibre-reinforced polymer (CFRP)/Ti6Al4V/aluminium stacks [34], for example, is evidence from cutting tools rather than from hot-work dies. The most suitable architecture is thus dependent on the specific context. Plants ought to start by using the smallest possible sensor set that will allow them to make an important decision, verify the model prospectively, and only add more complexity if this results in improved actionable performance.

VIII. RESEARCH GAPS AND FUTURE DIRECTIONS

Before intelligent tooling lifecycle management can become a regular practice in aluminium plants, several research gaps need to be filled. First, a priority is the development of shared, die-level benchmark data that connect production history to inspected damage and maintenance. The machining datasets used in the reviewed prognosis and monitoring work [15], [17], [26] do not by themselves validate models across aluminium die lifecycles. This review does not establish that suitable die datasets are entirely absent. For research into aluminium tooling it is necessary to have anonymised datasets that retain information about the geometry class, the material, the coating, the operating history, the inspection results, the maintenance events, and the quality outcomes. If these links are not maintained, then the models may predict process variability yet will be misinterpreted as die-health models.

Second, another priority is the modelling of spatial degradation. Damage from extrusion and die-casting takes place locally at the bearings, bridges, mandrels, gates, cooling sections, and other high-stress areas. Instead of having a single health score for each die,

future systems should produce spatial health maps based on simulation results, images, local temperatures, and inspection data. Using graph-based or mesh-based learning methods could allow the die's geometry to be represented directly and enable risks to be updated at key locations. If validated, these types of models could additionally support repair decisions by showing where intervention is needed rather than just when it is necessary.

Third, uncertainty should be an explicit output where it affects a decision. Prediction intervals or calibrated failure probabilities are more relevant to an individual tool than an un-explained confidence score. Gaussian-process models provide a probabilistic approach to wear prediction [31], while physical constraints can discourage behaviour inconsistent with the assumed mechanisms [26], [30]. Neither feature guarantees reliable uncertainty estimates outside the training domain. Future work should assess interval coverage and calibration on held-out tools and operating regimes, and distinguish measurement noise, model uncertainty and process variability where possible. A wide interval should trigger investigation; its width alone cannot identify whether the cause is sensor noise, limited training data or a change in operating conditions.

Fourth, maintenance activities have to be treated as status changes. Any action such as repair, polishing, welding, coating or re-nitriding will affect future degradation behaviour. The lifecycle model should estimate the association between inter-ventions and subsequent degradation, with controlled comparisons needed before attributing improvements to a particular action. Prescriptive maintenance would not only estimate re-maining life but also support decisions on whether to continue, repair, recondition or replace the tool, according to expected quality, cost and risk.

Fifth, validation should shift from relying on retrospective accuracy to involving prospective industrial trials. Model ver-sions should be fixed for each evaluation period and tested on previously unseen tools or production campaigns, with their performance assessed according to predefined decision criteria. Performance must be broken down by die family, alloy, product geometry, and operating regime. It is only on this basis that manufacturers can

determine whether a model is able to generalise beyond the historical dataset. Data splitting should keep observations from the same tool or production campaign together where appropriate to reduce leakage between training and test sets. Likewise, human factors need to be investigated: engineers should have interfaces that show the evidence, the uncertainty, and the recommended actions without causing automation bias.

A promising future approach is a hybrid decision-support system supported by a digital thread: connected information across the asset lifecycle. The digital thread would link to-gether the computer-aided die design, the simulation results, the records of tool manufacturing, the production signals, the inspection images, the maintenance work orders, and the qual-ity data all around a lasting asset identity. Physics-informed AI would estimate the degree of degradation; explainable models would display the evidence; uncertainty would regulate escalation; and the results of maintenance would update the knowledge base. Controlled updates and revalidation would be needed as the knowledge base grows. The CPMAI-based re-views in Section VI would connect this digital thread to named decision owners, approved operating scope and controlled changes. This represents a proposed path from individual AI demonstrations to intelligent lifecycle management.

The governance extension has additional limitations. PMI guidance supplies a lifecycle methodology, not evidence that these tooling controls improve die life or product quality. The proposed mappings, role assignments and review thresholds have not been validated with aluminium plants, assessed for CPMAI conformity or endorsed by PMI. Their feasibility depends on inspection capability, available expertise and reliable asset records. Future work should assess approval delays and governance effort alongside risk reduction, and distinguish compliance with a documented process from evidence that a tooling decision was technically sound.

IX. CONCLUSION

When applied as an engineering decision-making system rather than just as a standalone predictive exercise, artificial intelligence has the potential to

improve the way in which dies and tooling are managed over their lifetimes in the aluminium industry. The selected literature demonstrates capabilities relevant to several lifecycle stages: explainable models are able to make use of past design knowledge, process models can predict quality, methods combining multiple sensors and images can estimate wear, remaining-life models can aid in maintenance planning, and digital twins can align condition estimates with the current operational situation. Aluminium-specific studies show why thermal exposure, local geometry and wear mechanisms matter. The review proposes retaining maintenance history alongside these variables rather than assuming that repair restores an as-new condition.

The synthesis supports further evaluation of a hybrid architecture: physics supplies constraints and makes some mechanistic assumptions explicit; machine learning is able to represent nonlinear behaviour and variations specific to each process; the digital lifecycle keeps a record of the asset's history; and human supervision turns predictions into actions that can be accounted for. The CPMAI-based extension specifies iterative evidence reviews and separates model release, intervention approval and return-to-service authority. Decision records and reapproval after material changes connect this governance to the die genealogy. Future systems should report uncertainty, retain spatial and temporal context, and assess tool-life usage, scrap, downtime, quality and maintenance costs alongside decision traceability and review effort.

The proposed closed-loop lifecycle provides a framework for managing dies as traceable assets. The practical approach comprises making gradual steps: first establishing asset identity and data quality, then choosing sensors based on the main types of failure, checking the AI against engineering evidence, introducing probabilistic prognosis, and finally feeding all maintenance results back into design and process knowledge. Longer tool life, fewer unplanned interruptions and more consistent manufacturing are intended benefits, not outcomes demonstrated by this review. Prospective industrial trials are needed to determine whether the integrated framework achieves them while retaining engineering oversight.

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