



Artificial Intelligence as the New Intelligence Layer of Mechatronics: A Critical Review of the Transformation from Programmed Automation to Assured Autonomy

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Abstract: Mechatronics traditionally integrates mechanical systems, electronics, sensing and computer control through pre-specified models, rules and feedback structures. Artificial intelligence (AI) extends this paradigm by enabling representation learning, probabilistic inference, adaptive optimisation and data-driven decision-making; however, published evidence remains fragmented across robotics, maintenance, manufacturing, digital twins and cyber-physical systems. This critical evidence review synthesises a verified evidence core of 30 publications spanning 1997–2025 and defines a reproducible protocol for its future systematic extension. Records were classified by mechatronic function, AI method, application and study design; descriptive distributions and an evidence-density map were generated in Python without imputing missing performance data. The critical synthesis shows that the decisive architectural change is not the replacement of feedback control, but the addition of a learning and supervisory intelligence layer linking multimodal sensing, state estimation, prediction, planning and lifecycle optimisation. The strongest evidence concerns fault diagnosis, predictive maintenance, machine perception, data-enabled manufacturing and digital twins. AI-integrated systems offer context sensitivity, adaptation and decision support, whereas conventional systems retain advantages in determinism, certification, latency assurance and explainability. Quantitative cross-study effect pooling is presently unjustified because metrics, baselines, datasets and operating conditions are heterogeneous. Critical gaps concern real-time validation, uncertainty calibration, safety cases, cybersecurity, concept drift, interoperable data, energy-aware edge deployment and human authority allocation. The review proposes a function-based AI-Mechatronics Maturity Matrix that separates perception, estimation, prediction, decision, action and governance across five integration levels. The evidence supports hybrid, safety-bounded intelligence rather than unrestricted end-to-end autonomy as the most defensible near-term trajectory for industrial mechatronics and provides testable criteria for future comparative studies.

Index Terms: Artificial intelligence; Digital twins; Intelligent control; Mechatronics; Transformation of automation.

1. INTRODUCTION

Mechatronics emerged as a systems-engineering response to the increasing inseparability of mechanics, electronics, sensing, actuation and embedded control. Conventional implementations typically use engineered state variables, deterministic or stochastic models, fixed control structures, tuned gains, programmed sequences and threshold-based diagnostics. These systems can be precise and certifiable when operating conditions remain close to design assumptions, but performance generally depends on model fidelity, sensor quality and explicit anticipation of disturbances.

AI integration changes the information pathway. Learned representations can transform raw images, vibration, current, force and process histories into estimated states; predictive models can anticipate faults and remaining useful life; reinforcement learning and optimisation can select actions [1]; and digital twins can link asset data with simulation and lifecycle decisions. Cyber-physical manufacturing research therefore increasingly treats intelligence as a cross-layer capability rather than a standalone algorithm [2], [3], [4].

The literature is nonetheless structurally fragmented. Diagnostic accuracy studies often omit closed-loop implications; robotics papers may optimise benchmark success without industrial safety evidence; and digital-twin reviews report architectural promise while noting integration and deployment barriers. Recent maintenance syntheses explicitly identify discrepancies between academic demonstrations and industrial scale, data and model requirements [5], [6]. The need is therefore not another catalogue of algorithms, but a function-centred comparison showing where intelligence enters the mechatronic loop, what evidence supports its benefit, and which assurance obligations grow with autonomy.

1.1. Research questions

1. How does AI alter the sensing-estimation-decision-actuation-governance architecture of mechatronic systems?
2. Which AI families are associated with which mechatronic functions and application domains?
3. Which benefits are experimentally supported, and which remain architectural or prospective?
4. When are conventional model-based approaches preferable to learning-enabled approaches?
5. Which evidence gaps prevent safe, scalable and certifiable AI-enabled mechatronics?
6. Can integration maturity be assessed without conflating algorithmic sophistication with system-level assurance?

1.2. Review objectives

1. Classify AI contributions by mechatronic function and evidence type.
2. Compare conventional and AI-integrated systems in terms of technical and governance aspects.
3. Identify conditions under which reported improvements are externally valid.
4. Construct an evidence-density map and a non-imputing analytical dataset.
5. Propose a testable AI-Mechatronics Maturity Matrix.
6. Define a reproducible protocol for a 100+ record systematic update.

2. METHODOLOGY

2.1. Review design and search protocol

The completed component is a critical evidence-core synthesis. The reproducible extension should search Scopus, Web of Science Core Collection, IEEE Xplore, Engineering Village/Compendex, ScienceDirect and SpringerLink, supplemented by backward and forward citation chasing. A defensible search string is: (mechatronic* OR robot* OR cyber-physical OR “smart manufacturing” OR “digital twin*” OR “condition monitoring”) AND (“artificial intelligence” OR “machine learning” OR “deep learning” OR “reinforcement learning” OR “computer vision” OR “sensor fusion”) AND (control OR sensing OR maintenance OR optimisation OR autonomy OR manufacturing). Searches should record the database, exact query, fields, date, language and export count.

2.2. Eligibility and screening

Peer-reviewed journal articles, high-quality conference papers, and authoritative books or reviews that explicitly linked an AI technique to a physical mechatronic function or architecture were included. Studies focused solely on AI without demonstrable physical-system integration, purely mechanical design approaches lacking learning or inference capabilities, editorials without substantive technical synthesis, and records with inaccessible or unverifiable bibliographic metadata were excluded. The bibliographic corpus was screened thoroughly at the title/abstract and full-text stages.

2.3. Quality and data extraction

Extract verified bibliographic metadata, physical asset, sensors, sampling regime, AI method, comparator, split strategy, external validation, real-time deployment, hardware, latency, uncertainty, safety mechanism, cybersecurity consideration, metric definition and numerical result. Quality should be scored separately for internal validity, external validity, reproducibility, system integration and assurance. A model should not be labelled superior solely because it reports higher accuracy on a different dataset.

2.4. Quantitative rules

Publication growth may be computed as:

$$G_t = \left(\frac{N_t - N_{t-1}}{N_{t-1}} \right) \times 100 \quad (1)$$

where G_t is the percentage growth in the number of publications in year t ; N_t is the number of publications recorded in the current year t ; N_{t-1} is the number of publications recorded in the immediately preceding year $t - 1$; t denotes the current year of observation; and $t - 1$ denotes the year immediately preceding t . Equation (1) should be applied only when $N_{t-1} > 0$ and consecutive-year publication counts arise from a fixed, completed search conducted using consistent databases, search criteria and eligibility rules.

Comparative improvement may be computed as:

$$I = \left(\frac{P_{AI} - P_T}{P_T} \right) \times 100 \quad (2)$$

where I is the percentage improvement of the AI-integrated approach relative to the traditional or conventional approach; P_{AI} is the performance value obtained using the AI-integrated method; and P_T is the

corresponding performance value obtained using the traditional or conventional method. Equation (2) is valid only when $P_T \neq 0$, the directionality of the performance metric is aligned, and both P_{AI} and P_T are measured using the same metric, test dataset, experimental protocol and operating conditions. For benefit metrics in which a higher value indicates better performance, a positive value of I represents improvement. For error, cost, energy consumption, latency or other metrics in which a lower value indicates better performance, the direction of the calculation must be reversed or the resulting value must be interpreted accordingly. Because the present evidence core contains heterogeneous tasks, metrics, baselines, datasets and operating conditions, neither a pooled improvement value nor a meta-analytic effect size is reported.

For prospective system assessment, the proposed AI-Mechatronics Integration Maturity Index may be calculated as:

$$AMI = 25 \times \frac{\sum_{j=1}^m w_j s_j}{\sum_{j=1}^m w_j} \quad (3)$$

where AMI is the AI-Mechatronics Integration Maturity Index as shown in the Equation (3), expressed on a scale from 0 to 100; j is the index identifying each assessed mechatronic function; m is the total number of functions included in the assessment; s_j is the audited maturity score assigned to function j , where $s_j \in \{0, 1, 2, 3, 4\}$; w_j is the declared non-negative importance weight assigned to function j ; $\sum_{j=1}^m w_j s_j$ is the weighted sum of the audited maturity scores; $\sum_{j=1}^m w_j$ is the sum of the assigned importance weights; and 25 is the scaling factor that converts the maximum weighted mean maturity score of 4 to an index value of 100. The assessed functions are perception, state estimation, prediction, decision, action adaptation and governance; therefore, $m = 6$ in the proposed framework. The denominator must satisfy $\sum_{j=1}^m w_j > 0$. An AMI value of 0 indicates that all assessed functions have an audited maturity score of 0, whereas an AMI value of 100 indicates that all positively weighted functions have an audited maturity score of 4. The AMI is not a measure of system performance or evidence of the superiority of one system over another. It measures only the verified integration maturity of the assessed functions. Any application of the index must disclose the individual s_j scores, the corresponding w_j weights, the evidence supporting each score and the rationale used to assign the weights.

3. RESULTS AND DISCUSSION

The present dataset contains 30 evidence-core records. The counts reported in this section are properties only of this curated core and must not be interpreted as global bibliometric prevalence. Fig. 1. presents the distribution of the 30 records by publication year across the 1997–2025 coverage window. Therefore, Fig. 1. demonstrates the temporal coverage of the evidence core rather than the growth of the field; for this reason, Equation (1) is not applied to these counts, because a defensible growth analysis requires a comprehensive, frozen search and consistent indexing coverage. Fig. 2. complements this temporal view by showing how the same 30 records are distributed across the review themes.

Publication Distribution in the Verified Evidence Core

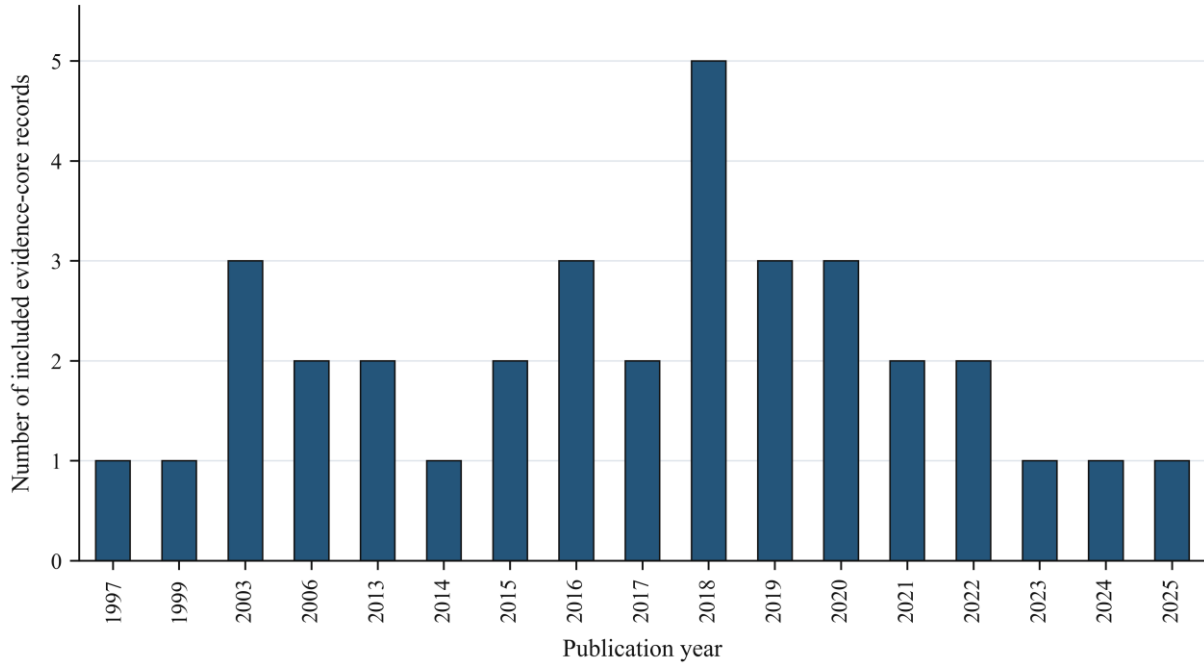


Fig. 1. Publication-year distribution of the 30 records in the verified evidence core.

Source: Original analysis of the 30-record evidence-core dataset; generated by the accompanying Python script.

Thematic Distribution of the Evidence Core

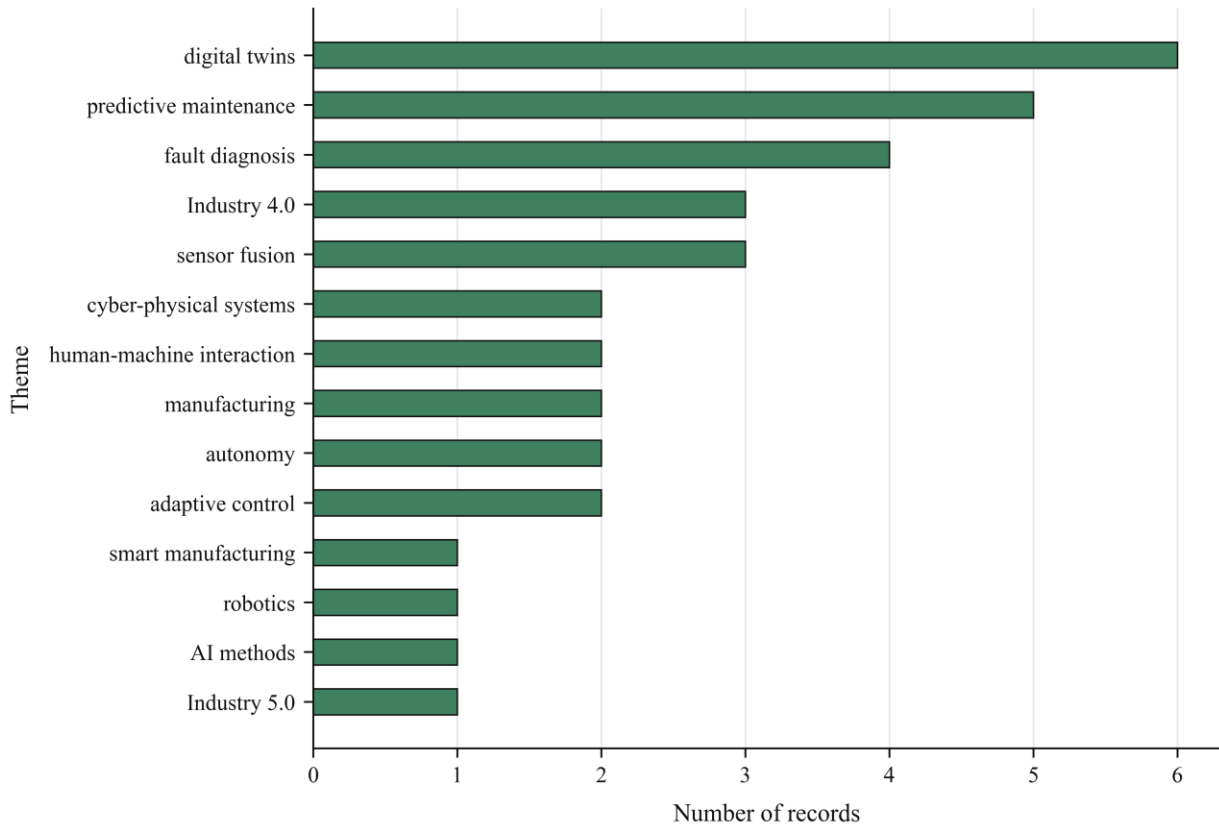


Fig. 2. Thematic distribution of the evidence core.

Source: Original analysis of the evidence-core dataset.

As Fig. 2. shows, digital twins, predictive maintenance and fault diagnosis are the most prominent themes in the core. They are deliberately prominent because these areas provide mature review literature connecting data-driven methods to physical assets; the distribution therefore reflects review construction and is not population prevalence. Fig. 3. cross-tabulates the same records by theme and study design, so that the type of evidence underlying each theme can be inspected.

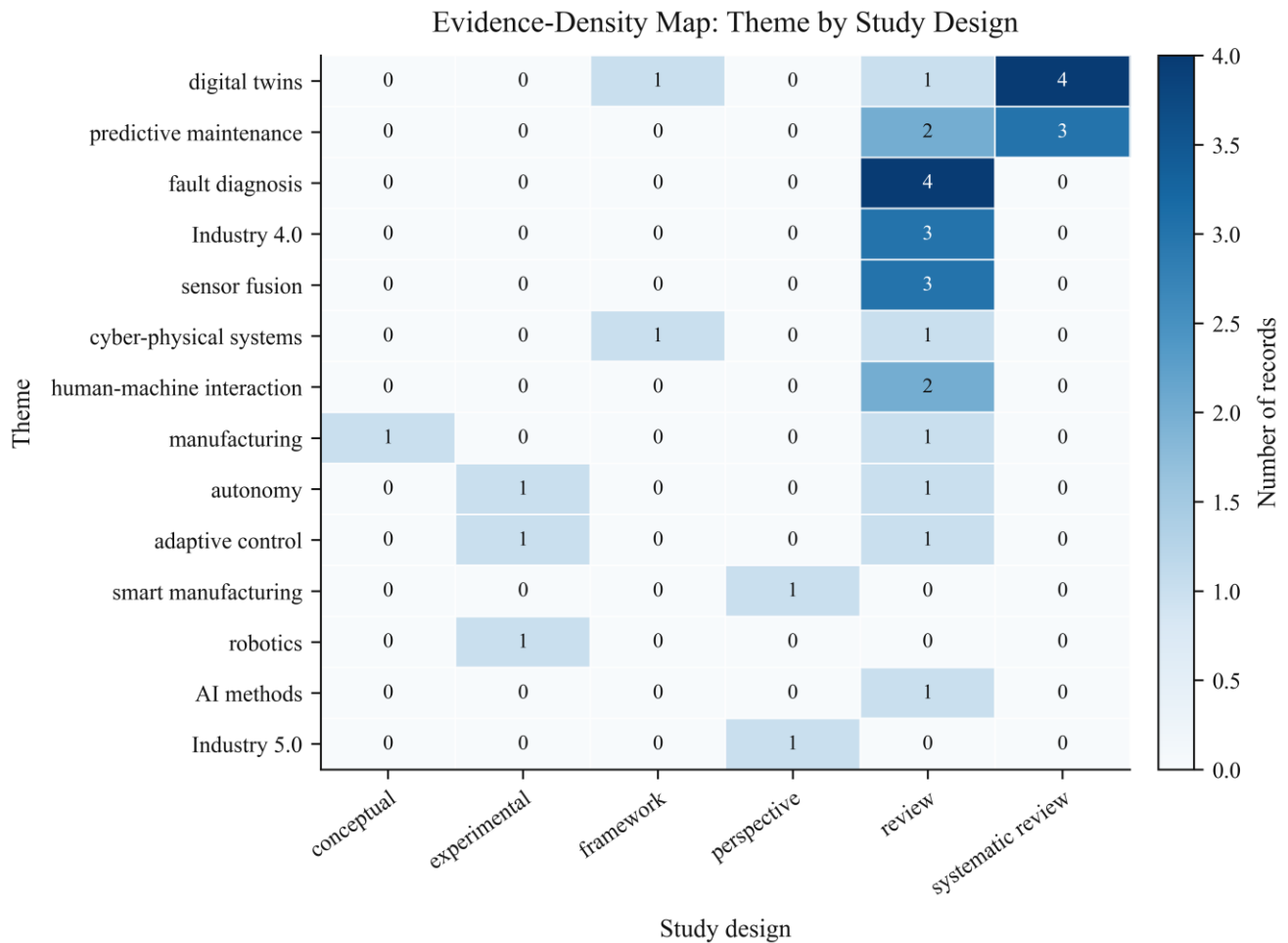


Fig. 3. Evidence-density map by theme and study design.

Source: Original analysis of the evidence-core dataset. Zero denotes no record in this core, not absence of research globally.

Fig. 3. exposes the central evidence imbalance: reviews and frameworks are more common than system-level experimental demonstrations in this core. This distinction prevents architectural possibility from being misreported as industrially validated benefit, and it frames the comparison in Section 3.1.

3.1. Conventional versus AI-integrated mechatronics

Table 1. compares conventional and AI-integrated mechatronics across 22 dimensions, spanning control, decision-making, sensing, autonomy, maintenance, manufacturing, human-machine interaction, assurance and lifecycle considerations. For each dimension, the final column records the critical qualification that the synthesised literature attaches to the AI-integrated capability, so that each reported capability gain is read together with the obligation it creates.

Table 1. Evidence-bounded comparison of conventional and AI-integrated mechatronics

Dimension	Conventional	AI-integrated	Critical qualification
Control	Model-based/fixed-gain or gain-scheduled loops	Learning augments identification, adaptation, tuning or supervisory policy	AI does not remove stability and safety obligations
Decision-making	Rules, state machines, optimisation with fixed models	Data-driven prediction, probabilistic inference and learned policies	Distribution shift can invalidate decisions
Sensing	Calibrated sensors with engineered preprocessing	Learned perception and multimodal feature extraction	Data quality and calibration remain foundational
Data processing	Low-dimensional features; local filtering	High-dimensional streaming analytics; edge/cloud pipelines	Latency, bandwidth and energy costs rise
Adaptability	Pre-programmed modes and retuning	Online or periodic learning and context adaptation	Uncontrolled adaptation complicates certification
Autonomy	Bounded sequences under explicit logic	Perception-planning-action loops with reduced intervention	Safe fallback and authority allocation are required
Fault detection	Thresholds, residuals and expert rules	Anomaly detection, classifiers and prognostics	False alarms and domain transfer remain concerns
Predictive maintenance	Reactive/time-based maintenance	Condition-based prediction of degradation and RUL	Industrial labels and run-to-failure data are scarce
Optimisation	Offline deterministic/stochastic optimisation	Surrogate, evolutionary and learning-based online optimisation	Feasibility constraints must be enforced
Machine vision	Hand-crafted features and geometric rules	Deep-learned detection, segmentation and pose estimation	Generalisation depends on representative data
Robotics	Programmed trajectories and model-based control	Learning from data, demonstration and interaction	Benchmark gains may not transfer to factories
Human-machine interaction	Fixed interfaces and safety separation	Context-aware assistance and collaborative adaptation	Trust, workload and human authority need evaluation
Manufacturing	Hierarchical automation and isolated cells	Connected CPS, analytics, twins and adaptive orchestration	Legacy integration and interoperability constrain scale
Energy efficiency	Design-time optimisation and fixed schedules	Forecasting and adaptive energy-aware scheduling	Inference energy can offset savings

Dimension	Conventional	AI-integrated	Critical qualification
Reliability	Validated components and predictable failure modes	Prediction can improve maintenance decisions	AI adds software/data failure modes
Precision	Calibration and high-bandwidth feedback	Learned compensation, perception and disturbance estimation	Benefits are application- and dataset-specific
Response time	Deterministic real-time execution	Potentially richer but computationally heavier inference	Worst-case latency needs explicit assurance
Learning capability	None or limited adaptive identification	Offline, transfer, continual or reinforcement learning	Catastrophic forgetting and drift require controls
System complexity	Modular physical/control integration	Adds data, models, MLOps, connectivity and monitoring	Lifecycle complexity increases
Cybersecurity	Embedded/industrial-control attack surface	Larger attack surface plus adversarial/data-poisoning risks	Secure update and provenance become essential
Explainability	Models and rules often interpretable	Opaque high-capacity models may dominate perception	Explanation must support engineering decisions
Scalability	Replication of engineered configurations	Fleet learning and reusable analytics are possible	Heterogeneous assets limit transfer

Source: Synthesised from Hall and Llinas [7], Jardine et al. [8], Kober et al. [9], Lee et al. [2], Wuest et al. [10], Tao et al. [4], Villani et al. [11], Carvalho et al. [12], Jones et al. [13], and Chen et al. [6].

As Table 1. indicates, AI integration consistently extends capability in sensing, prediction, adaptation and decision support, whereas the qualification column shows that each extension introduces a corresponding validation, assurance or lifecycle obligation. These qualifications are examined theme by theme in Section 4.

4. CRITICAL THEMATIC SYNTHESIS

4.1. Control, adaptation and autonomy

Reinforcement learning expands control from parameter adaptation to policy learning, but the physical-system problem differs from game benchmarks because exploration can damage equipment and violate safety constraints. Kober et al. [9] therefore frame robotics learning around sample efficiency, generalisation and the use of prior knowledge. Deep reinforcement learning demonstrated powerful representation-control coupling in benchmark environments [14], robot-learning studies showed end-to-end visual-motor training [15], and field robotics demonstrated learned perception integrated with planning and control in the autonomous vehicle Stanley [16]. The defensible engineering synthesis is hybrid: retain stabilising model-based inner loops and verified constraints, while using learning for estimation, adaptation or supervisory decisions.

4.2. Intelligent sensing and sensor fusion

Classical multisensor fusion formalises association, uncertainty and state estimation [7], [17], and simultaneous localisation and mapping research extends this estimation problem towards robust perception in robotics [18]. Deep learning adds hierarchical representation learning for images and heterogeneous sensor streams, but does not remove observability, synchronisation or calibration requirements. In safety-critical systems, confidence calibration and graceful degradation are as important as mean predictive accuracy.

4.3. Fault diagnosis and predictive maintenance

The process-fault literature established knowledge-based, qualitative-model and neural/statistical families before current deep-learning practice [19], [20], [21]. Condition-based maintenance then linked diagnostics, prognostics and maintenance decisions [8]. Later reviews document extensive use of machine learning and deep learning [12], [22], [23]. The remaining bottleneck is not merely classifier choice. It is validity under changing loads, sparse failures, fleet heterogeneity and asymmetric consequences of missed detections and false alarms.

4.4. Manufacturing, CPS and digital twins

Smart manufacturing joins physical equipment, communication, data models and analytics [24], [2], [3], and Industry 4.0 surveys frame this integration as the basis of connected, data-driven production [25], [26]; earlier research on reconfigurable manufacturing systems had already argued for modular, rapidly adaptable production architectures [27]. Digital twins extend this integration through persistent virtual representations and data exchange [28], [13], [4]. Recent maintenance reviews support a layered interpretation that includes physical assets, transmission, twin models, AI analytics and services, while also reporting scale, data and model gaps between research and practice [6].

4.5. Human-machine systems and Industry 5.0

Collaborative robotics changes the design objective from autonomous replacement to joint performance. Reviews emphasise safe physical interaction, task allocation, interfaces and adaptive assistance [29], [11]. Industry 5.0 arguments add human-centricity and resilience [30]. Adaptive behaviour should therefore be assessed not only by cycle time or accuracy, but also by authority clarity, workload, predictability and recoverability.

5. PROPOSED AI-MECHATRONICS MATURITY MATRIX

Building on the qualifications in Table 1. and the thematic synthesis in Section 4, Table 2. presents the proposed AI-Mechatronics Maturity Matrix. It defines five integration levels, from Level 0 (conventional) to Level 4 (supervisory autonomous), each specified by an operational criterion and an illustrative system form. These levels provide the ordinal 0–4 scale on which the function-level scores s_j in Equation (3) are audited.

Table 2. AI-Mechatronics Maturity Matrix

Level	Operational criterion	Illustrative system form
0: Conventional	No learned component in operational loop	Engineered sensing; model/rule control; manual maintenance
1: Assisted	Offline AI informs engineers but does not execute action	Inspection classifier; maintenance recommendation
2: Embedded	AI performs bounded perception/estimation inside verified architecture	Vision-based state estimate with deterministic fallback
3: Adaptive	AI changes parameters or schedules under monitored constraints	Adaptive tuning; condition-based maintenance optimisation
4: Supervisory autonomous	AI coordinates prediction, planning and action with assurance and human override	Twin-supported fleet optimisation with safety envelope

Source: Proposed by this review. Levels describe verified integration and governance, not claimed performance superiority.

As Table 2. shows, the framework's novelty is the separation of functional intelligence from assurance maturity. A system cannot reach Level 4 merely by using a sophisticated neural network. It must show bounded action authority, monitored uncertainty, fallback behaviour, data/model provenance, cybersecurity controls and lifecycle validation. This prevents algorithm novelty from being mistaken for mechatronic autonomy.

6. RESEARCH GAPS AND AGENDA

Table 3. consolidates the principal evidence gaps identified in Sections 3 and 4. For each gap, it states the problem observed in the current literature and the research design required to address it, thereby converting the critical qualifications in Table 1. and the assurance conditions of Table 2. into testable study requirements.

Table 3. Evidence-derived research gaps and testable responses

Gap	Observed problem	Required research design
Real-time external validation	Few cross-site, long-duration studies report worst-case latency, drift and failure recovery.	Multi-site prospective trials with frozen protocols and hardware timing.
Comparable baselines	Metrics and baselines differ across datasets and conditions.	Report paired conventional and AI baselines on identical test streams.
Safety and uncertainty	Accuracy is often separated from risk and calibration.	Report calibrated uncertainty, hazard-linked thresholds and fallback tests.
Lifecycle MLOps	Model update, rollback and provenance are under-documented.	Audit data lineage, versioning, monitoring and controlled revalidation.
Cybersecurity	AI and connectivity enlarge attack surfaces.	Joint safety-security threat models, poisoning tests and secure update mechanisms.
Human authority	Automation performance may ignore workload and controllability.	Evaluate authority transitions, comprehension, workload and recovery.
Energy and hardware	Inference cost is seldom integrated with system efficiency.	Measure energy, memory, bandwidth and thermal effects at the edge.

Gap	Observed problem	Required research design
Standardisation	Twin semantics and interfaces remain heterogeneous.	Validate interoperable asset, data and assurance models.

Source: Derived by this review from the evidence-core synthesis in Sections 3 and 4.

Together, the eight gaps in Table 3. show that the dominant deficit is system-level rather than algorithmic; the recommendations in Section 7 translate the required research designs into design and reporting practices.

7. RECOMMENDATIONS

1. Use paired, identical-condition comparisons against tuned conventional baselines.
2. Preserve physics-based constraints and deterministic safety layers around learning components.
3. Report uncertainty calibration, worst-case latency, energy and recovery, not accuracy alone.
4. Publish machine-readable metadata, data provenance, code and model versions where legally possible.
5. Validate across assets, sites, operators and time to test transfer and drift.
6. Treat cybersecurity, human authority and lifecycle revalidation as architecture-level requirements.
7. Use the maturity matrix only with auditable evidence and declared weights.

8. LIMITATIONS

This review is limited by its selective 30-publication evidence core and by substantial heterogeneity in systems, datasets, metrics, baselines and validation conditions, which prevented quantitative pooling and limits generalisability to industrial deployment. Evidence for long-term real-time operation, cross-site transferability, uncertainty, safety, cybersecurity and computational performance remains insufficient, while the proposed AI-Mechatronics Maturity Matrix requires independent empirical validation and reliability testing.

9. CONCLUSION

AI has transformed mechatronics chiefly by adding learning-enabled perception, prediction and supervisory decision layers to the conventional sensing-control-actuation loop, thereby extending adaptation, maintenance intelligence, machine vision, digital-twin services and bounded autonomy. The evidence does not support a universal numerical superiority claim because experimental baselines, metrics and operating conditions remain heterogeneous; conventional control retains decisive advantages in deterministic timing, interpretability and certification. The principal gap is system-level, long-duration validation that jointly measures performance, uncertainty, latency, safety, cybersecurity, energy and human authority. This review contributes a function-based AI-Mechatronics Maturity Matrix that distinguishes integration sophistication from assurance maturity and supports a hybrid trajectory in which learning is constrained by physical models, safety envelopes, monitored uncertainty and recoverable human oversight.

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