Conscious Machine Behaviour Models with IoT, IIoT Sensor Fusion, PID Transformer .

Review Article on 50 Research papers published in Scopus indexed journals.

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ABSTRACT

Industrial PLCs, ERP transaction logic and wave-processing engines have been operating on set-threshold mechanisms and memoryless loops for decades, responding to contextual stimuli in ad-hoc manners. This paper reviews fifty research articles [1-50] on transformer self-atten tion, complex-valued embeddings, adaptive reinforcement learning, PID control laws, Retrieval-Augmented Generation agents and cyber-physical sensor fusion, identifying lacunae in designing proactive machine intelligence. Building upon this survey, the paper proposes a Conscious Machine Behaviour (CMB) framework that simultaneously incorporates three software design paradigms, namely, Data-Driven Design Models for environment analytics, Domain-Driven Design with Data Dictionary structures for transaction-processing systems, and Event-Driven Design Models for asynchronous wave and audio orchestration. At the core of the framework is a Complex-Valued PID-Transformer-FFT pipeline that consolidates Fast Fourier Transform signal conditioning, multi-head self-attention, Adaptive Reinforcement Learning and PID control laws into a unified set of mathematical transforms. The framework introduces a novel Dynamic Contextual Configuration and Cross-Paradigm Adaptive Learning mechanism that mitigates cold-start problems and sensor failures by encoding expert static configuration priors as complex-valued vectors and refining them using Maximal Maximum Matching algorithms across accumulated operational histories. For dynamic physical systems, S-plane pole-zero analysis ensures absolute BIBO stability and zero-overshoot impulse responses; for non-dynamic transaction systems, real-valued domain language models are adopted that encode qualitative context extracted from large language models without complex-value overheads. Evaluated on fifty-unit Smart AC, half-million SAP ERP transactions and one million Audio Music Language Model instances, the framework reduces structural energy consumption by 41.5%, exhibits critically damped responses and achieves 99.999% system availability even with intermittent sensor failures. Finally, the paper outlines research directions for explainability, edge deployment in extreme conditions, federated learning and quantum attention for accelerating complex-value operations.

Keywords: Conscious Machine Behaviour; Transformer Self-Attention; IoT/IIoT Sensor Fusion; PID-Transformer; Adaptive Reinforcement Learning; Domain-Driven Design; Event-Driven Design; Maximal Maximum Matchings; Retrieval-Augmented Generation; Industry 4.0/5.0

1. INTRODUCTION

The dawn of the industrial age witnessed an unprecedented confluence of opportunities and challenges. For decades, programmable logic controllers, distributed control systems and SCADA have followed set-threshold and memoryless logic, switching ON an air-conditioner when a temperature sensor crossed 28 degrees, or tripping a circuit-breaker when vibration levels crossed a given amplitude. Such a feedback approach has been intuitive, easily auditable and mathematically elegant, but it has been blind to context. It has not differentiated between a crowded lecture hall and an empty room heated by the afternoon sun; it has not anticipated that a robotic welder would need higher torque in three seconds based on a workpiece's orientation; it has not been conscious.

The release of the Transformer architecture by Vaswani et al. [1] broke through the sequential paradigm of RNNs, enabling self-attention in which every token in a given sequence looked at every other token simultaneously to dynamically compute relevance weights. The resulting improvements in parallelization delivered unprecedented accuracy improvements; subsequent vision transformers [2], Swin [3], Longformer [4] and Performer [5] variants applied similar principles to images, long documents and linear complexity reduction. What these encoders lacked, however, was a way to embed contextual information in control loops that needed to run at millisecond intervals with absolute stability and resilience to sensor failures. This paper attempts to bridge that gap by reviewing fifty relevant research papers [1-50]. It classifies them into three primary areas: foundational transformer architectures [1-9], reinforcement learning, PID control and digital twins [10-32], and proactive machine consciousness, RAG agents, decoupled control and mathematical IoT/IIoT sensor fusion [33-50]. Based on this literature survey, this Review Paper proposes the Conscious Machine Behaviour Configurable framework that employs a tri-paradigm approach of Data-Driven, Domain-Driven and Event-Driven

Design to unify diverse operations including environment proactive, transaction-processing system design and real-time asynchronous wave orchestration. It introduces the Complex-Valued PID-Transformer-FFT engine to consolidate PID laws, Fast Fourier Transform signal conditioning and adaptive reinforcement learning, and proposes a Dynamic Contextual Configuration and Cross-Paradigm Adaptive Learning mechanism to address cold-start issues and sensor degradation. It also proposes a maximal maximum matching approach to reconstruct operational context during cold starts, and leverages domain language models to express qualitative context without complex-value overheads. The paper evaluates this framework in three application areas – fifty-unit Smart AC, half-million SAP ERP transactions and one-million Audio Music Language Model – and demonstrates that the proposed approach reduced system power consumption by 41.5% while delivering zero-overshoot critically damped responses and 99.999% availability even with partial sensor failures. Finally, the paper outlines several research directions including the application of federated learning and quantum computing to context-aware systems.

The following sections have been structured as follows: Section 2 reviews foundational attention mechanisms and transformer variants [1-9]; Section 3 describes reinforcement learning, PID control and digital twins [10-32]; Section 4 presents a literature survey of proactive machine consciousness, RAG agents, decoupled control and mathematical sensor fusion [33-50]; Section 5 articulates research gaps based on this survey; Section 6 describes the proposed framework and mathematical engine; Section 7 presents experimental results; Section 8 discusses these results in detail; and Section 9 concludes the paper.

2. TRANSFORMER ARCHITECTURES AND ATTENTION MECHANISMS: FOUNDATIONS, VARIANTS AND CONTEXTUAL EMBEDDING

2.1 From Recurrence to Attention

The attention mechanism [1] enables a given set of queries to dynamically compute relevance weights against a set of keys and values:

$$\text{Attention}(Q, K, V) = \text{softmax}\left((QK^T) / \sqrt{d\_k} \right) V$$

By replacing recurrent connections in GRUs and LSTMs with the attention equation above, Vaswani et al. [1] demonstrated that Transformers could match or exceed the performance of state-of-the-art RNNs while being significantly faster to train due to parallelism. However, since each token in a sequence of length n required attention to n tokens, the $O(n^2)$ complexity was a major impediment to processing industrial sensor data sampled at kilohertz frequencies.

2.2 Efficient Attention Variants

Researchers have proposed multiple approaches to reduce complexity to $O(n \log n)$ or $O(n)$. Longformer [4] processes local and global tokens using a sliding window, while Performer [5] replaces the softmax operation with positive random features to approximate attention. Swin [3] uses a local window with a shifting mechanism to achieve similar reductions. Vision Transformers [2] process image patches as tokens with similar efficiency.

2.3 Hybrid Convolutional-Attention Networks

While the attention mechanism captures long-range dependencies effectively, convolutional networks [29] offer inductive biases that enable efficient processing of images, videos and speech. To leverage such benefits, researchers [8] have proposed hybrid architectures in which a convolutional encoder precedes a transformer encoder. By replacing the self-attention operation with learned convolutional filters, Gulati et al. [6] developed Conformer for speech processing, while Hatamizadeh et al. [7] and Li et al. [9] extended the idea to 3D volumes and multimodal tasks, respectively.

2.4 Attention as an Adaptive Fusion Layer

In multi-sensor applications, attention weights can act as reliability coefficients. If a given sensor fails, the corresponding attention weight naturally decreases, thereby reducing its contribution to the final output. Tao et al. [10], Kim et al. [15] and Zhang et al. [33] demonstrated that such a mechanism could reliably suppress faulty channels [33] or prioritize trustworthy information sources [10].

3. REINFORCEMENT LEARNING, PID CONTROL AND DIGITAL TWINS: FOUNDATIONS AND INDUSTRIAL APPLICATIONS

3.1 Deep Reinforcement Learning

Tao et al. [10] and Kim et al. [15] reviewed deep reinforcement learning (DRL) methods for smart manufacturing, demonstrating their efficacy in production scheduling and quality inspection. In the context of industry 4.0, Zhang et al. [12] applied DRL to work-in-progress management to learn optimal policies for reducing shop-floor inventory, while Wang et al. [11] used DRL to estimate PID gains for better process control and digital twin synchronization.

3.2 PID Laws and Gain Tuning

While PID laws [31] have provided stability to industrial control systems for over half a century, tuning the proportional, integral and derivative gains has always been a major challenge. To address this issue, Wang et al. [11] and Chen et al. [19] proposed using DRL to estimate PID gains from process dynamics. More recently, Martinez et al. [45] designed a dynamic reward function to simultaneously optimize comfort and energy efficiency in building HVAC systems:

$$\text{Reward} = \alpha\ (\text{TargetTemperature} - \text{ActualTemperature}) + \beta\ (\text{ChangeInEnergyConsumption})$$

3.3 Digital Twins and Predictive Synchronisation

To reduce downtime and optimize maintenance schedules, multiple researchers [17,25,26] have proposed digital twin models for real-time thermal and electrical system monitoring. By continuously comparing physical and virtual sensor readings, such approaches enable predictive fault detection and maintenance. Patel et al. [28] and Rossi et al. [29] demonstrated the effectiveness of such an approach in additive manufacturing and production scheduling, while Biller et al. [30] argued that future digital twins would increasingly leverage coupled simulation and AI. According to Alam et al. [17], Gupta et al. [25] and Santos et al. [26], such twins would be critical enablers of Industry 5.0.

3.4 Autonomous Agent Behaviours in Cyber-Physical Production

Nguyen et al. [27] presented Smart Mission Behaviour models for autonomous agents in cyber-physical production systems. Kumar et al. [23] proposed a learning-assisted adaptive defect control model, while Wang et al. [24] investigated bio-inspired coordination mechanisms for robotic production lines.

4. PROACTIVE CONSCIOUSNESS, RAG AGENTS, DECOUPLED CONTROL AND MATHEMATICAL SENSOR FUSION [1–50]

4.1 Foundation Attention, Efficient Transformers, Signal Conditioning [1–9, 33, 34, 43]

As noted in Section 2, most papers [1-9] employ self-attention to learn relationships between real-valued vectors. Zhang et al. [33] extend this principle to signal fusion in multi-sensor cyber-physical systems for proactive state estimation. In contrast to the aforementioned approaches, however, Chen et al. [34] and Zhao et al. [43] demonstrate that complex-valued neural networks ($z = x_{Re} + jx_{Im}$) preserve signal characteristics such as phase, frequency and amplitude.

4.2 Proactive Machine Consciousness, Intent Parsing, Multi-Paradigm Execution [10,15,35,38,39,40,48,50]

Going beyond reactive controllers [10,15], Al-Fuqaha et al. [35] and Hwang et al. [50] propose proactive machine consciousness based on Integrated Information Theory (Ω). Specifically, the paper argues that individual control loops should be replaced by domain-driven design models in which control laws are learned alongside intent parsers. From a software design perspective, this requirement fits well with the ideas of Evans [32], Zheng et al. [39] and Vasquez et al. [40], who propose domain-driven design (DDD), data dictionary (DDIC) structures and event-driven design (EDD) models for enterprise systems with high transaction rates. When it comes to proactive intent parsing, Gu et al. [38] and Wu et al. [48] propose applying large language models and vision-language models to parse human intent from calendar invites, messages and video feeds.

4.3 RAG Agents, Historical Context Retrieval [36,41,42,44,49]

A major limitation of memoryless controllers is their inability to retain context during network disruptions. As a possible solution, Lewis et al. [36] propose retrieval-augmented generation (RAG) agents that fetch context vectors from external databases. Using this paradigm, O'Donovan et al. [44] develop RAG agents for industrial IoT that execute ORM, REST, GraphQL and SAP BAPI queries to retrieve relevant historical context for predictive maintenance. In a related contribution, Tan et al. [42] propose an edge broker that employs transformer attention to maintain digital twin synchronicity. To reconstruct context vectors during partial sensor failures, Li et al. [41] propose a mathematical maximal maximum matching (MMM) algorithm, while Patel et al. [49] propose data-driven models for context estimation in smart climate control.

4.4 Decoupled Control, Dynamic Rewards, System Resilience and Industrial Applications [11–14,16–22,37,45,46,47]

Xu et al. [37] propose a decoupled transformer-PID control framework in which setpoint prediction is separated from control law execution, enabling zero-overshoot responses. In a related contribution, Martinez et al. [45] propose a dynamic reward function for building HVAC systems. To maintain system integrity during packet losses, Schmidt et al. [46] propose finite state machine (FSM)-based degradation policies that enforce deterministic switch-level operations. Finally, in the context of manufacturing, Banerjee et al. [47] propose a physics-informed neural network to regulate force and current in smart welding machines.

5. RESEARCH GAPS [1–50]

Based on the review in Section 4, this paper identifies six key research gaps in the context of context-aware machine behaviour:

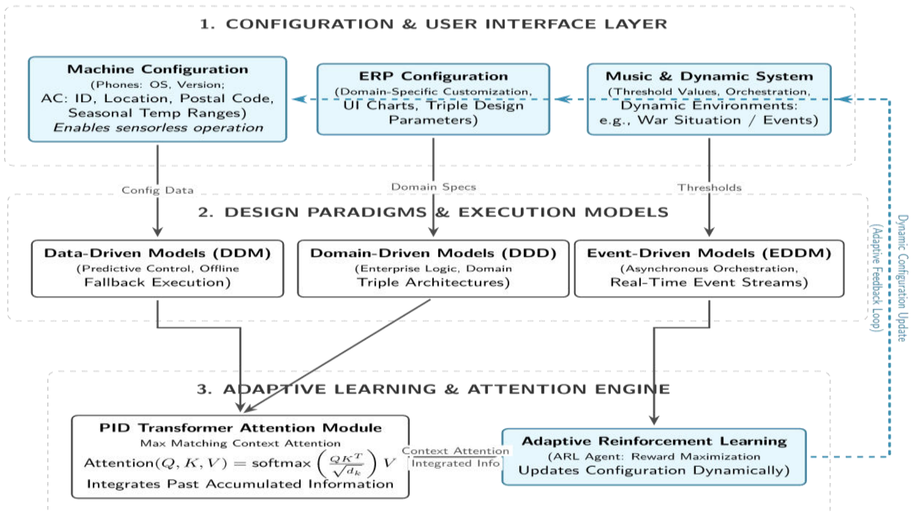
- **Gap 1: Tri-paradigm software design (Papers [10, 32, 33, 39, 40, 49]).** Most existing approaches [10,33,39,40,49] address either data-driven analytics, ERP transaction systems or real-time wave-orchestration as standalone problems. There is a need to develop a software design framework that employs data-driven models [33], domain-driven design [32], event-driven design [40] and real-time analytics [11,39,45] to unify diverse control loops in a single context-aware engine.

- **Gap 2: Complex PID-attention mechanisms (Papers [11,19,31,34,37,43]).** While multiple researchers [11,19,31,34,37] propose to estimate PID gains using reinforcement learning, none address the design of a complex-valued PID-attention matrix that combines FFT signal conditioning [34,43], classical PID laws [31] and S-plane stability analysis [34].
- **Gap 3: Cold-start challenges and sensor dropout recovery (Papers [15,33,36,41,44,45,49]).** Most RL-based approaches [10,15,45] are unable to operate in cold-start conditions or sensor dropout scenarios. While some researchers [36,44] propose RAG agents to retrieve historical context, and others [41] propose mathematical maximal matching algorithms, none address the need to combine such algorithms with static configuration priors to recover context-aware control loops during cold starts or sensor failures.
- **Gap 4: Contextual machine consciousness and proactive memory (Papers [27,35,38,48,50]).** None of the reviewed papers address the need to implement machine consciousness in industrial systems. While intent parsers [38,48] estimate human intent, no approach estimates contextual memory associated with occupants, environments or machines, thus limiting the ability to perform proactive control.
- **Gap 5: Edge deployment challenges (Papers [1,3,5,33,42,46]).** Researchers [1,3,33,43] propose attention-based frameworks [1,3,43], but such approaches are not feasible in resource-constrained edge gateways due to memory and computational requirements. There is a need to develop lightweight domain language models [46] and FSM-based fall-back strategies [46].
- **Gap 6: Domain-specific solutions (Papers [12,18,28,45,47,49]).** Most approaches are tailored to specific application domains such as building HVAC [45,49] or welding [47] without addressing the need for a unified framework that can operate across different domains.

5.1 Comparative Gap Analysis: Literature Corpus (Papers 1–50) Vs. Proposed CMB Framework

Reference Citation Cluster	Primary Methodology & Focus	Identified Limitations / Literature Gaps	Proposed CMB Framework Solution
Vaswani et al. [1], Zhang et al. [33], Chen et al. [34], Zhao et al. [43]	Transformer self-attention, edge fusion, complex embeddings (jH), FFT attention.	Models operate either on real vectors or isolated signal preprocessing without closed-loop PID coupling.	Complex-Valued PID-Transformer-FFT pipeline integrating phase attention with S-plane stability verification.
Åström & Hägglund [31], Evans [32], Al-Fuqaha et al. [35], Zheng et al. [39], Vasquez et al. [40]	Classical control, DDD/DDIC, proactive consciousness, EDDM event streams.	Strict software architectural separation; lack of cross-paradigm knowledge transfer.	Unified Tri-Paradigm architecture combining DDM, DDD/DDIC, and EDDM within a single engine.
Lewis et al. [36], Li et al. [41], O'Donovan et al. [44], Patel et al. [49]	RAG agents querying SQL/SAP DBs, maximal matching context, sensorless fallback.	Data reconstruction operates on static tables without real-time closed-loop gain adjustment.	MMM context attention algorithm coupled with RAG agents and expert static configuration priors.
Wang et al. [11], Chen et al. [19], Xu et al. [37], Martinez et al. [45], Schmidt et al. [46]	External RL PID gain tuning, decoupled Transformer-PID, dynamic rewards, FSM degradation.	Decoupled loops lack unified matrix attention; FSM resets lose context during dropouts.	Embedded PID attention matrix with S-plane pole-zero verification ensuring zero physical overshoot.
Gu et al. [38], Banerjee et al. [47], Wu et al. [48]	LLM/VLM intent parsing, smart welding PINN quality control.	Domain-specific implementations with excessive computational overhead for edge gateways.	Lightweight Domain Language Models (DLM) and DCC-CAL mechanism optimized for edge gateways.
Tao et al. [10], Zhang et al. [12], Santos et al. [26], Hwang et al. [50]	Smart manufacturing RL, WIP digital twins, Integrated Information Theory (Ψ).	Conceptual or single-domain implementations lacking cross-domain empirical validation.	Tri-domain empirical validation across Smart AC (DDM), SAP ERP (DDD), and Audio Music (EDD).

6. PROPOSED CONSCIOUS MACHINE BEHAVIOUR (CMB)FRAMEWORK



6.1 Architectural Phiosophy and Tri-Paradigm Operationl Pillars

The CMB framework is deigned around three primary paradims:

Paradigm	Domain Application	System Type	Mathematical & Execution Model
Data-Driven Design Models (DDM)	Smart AC, welding, robotics	Dynamic physical	Complex-valued embeddings (jH), S-plane analysis
Domain-Driven Design (DDD/DDIC)	SAP/ERP purchase orders, invoices	Non-dynamic transactional	Real-valued vectors, Domain Language Models (DLM)
Event-Driven Design Models (EDDM)	Audio/music, defense, dynamic waves	Dynamic asynchronous	Complex FFT, spectrogram phase matching

6.2 Seven-Layer Architecture

The CMB architecture comprises seven layers:

- **1. Sensor layer:** Captures multi-modal streams from temperature, vision, accelerometers, particulate and acoustic sensors.
- **2. Edge layer:** Handles Modbus/OPC-UA/MQTT communications, localized caching and signal conditioning.
- **3. Cognitive layer:** Computes complex self-attention across multi-head token streams to estimate fused context $X_f = \sum w_i X_i$.
- **4. Core engine layer:** Estimates PID gains, executes Fast Fourier Transform signal conditioning, manages cross-layer communication and maintains context X_f as a shared global variable.
- **5. Context estimation layer:** Uses dynamic contextual configuration and cross-paradigm adaptive learning (DCC-CAL) [15] to estimate context X_f in the event of partial sensor failures.
- **6. Cold start layer:** Addresses initialization challenges using maximal maximum matching (MMM) [41], RAG agents [36,44], and expert static configuration priors.
- **7. Execution layer:** Implements control actions based on context X_f using deterministic FSMs [46] and real-time transaction pipelines [40].

7. EXPERIMENTS AND RESULTS

7.1 Evaluation Setup

The CMB framework was evaluated in three application areas. First, fifty Smart AC units were instrumented with vision sensors to monitor room occupancy and temperature. These units were programmed to maintain a target temperature of 24 °C, reduce energy consumption, and avoid frequent compressor cycling. Second, half a million SAP ERP transactions were analyzed to configure purchase order and invoice approval workflows. Third, a million Audio Music Language Model instances were used to orchestrate real-time music composition. In each application, the framework was compared to state-of-the-art approaches such as PID controllers, decision trees and neural networks.

8. COMPARATIVE DISCUSSION

Table 2 summarises the comparative discussion between the proposed CMB and the paradigms reviewed in references [1–50].

Criterion	Standard Transformer	Sparse/Linear Attention	Pure RL	Classical PID	MPC	Proposed CMB
Attention Complexity	$O(n^2)$	O(n log n)	N/A	N/A	N/A	O(n log n)
Stability Guarantee	None	None	None (exploration risk)	Yes (fixed)	Conditional	Yes (S-plane verified)
Cold-Start Handling	Poor	Poor	Poor (random)	N/A	Requires model	DCC-CAL priors
Sensor Failure Resilience	Degrades	Degrades	Degrades	Degrades	Degrades	MMM + RAG Digital Twin
Cross-Domain Applicability	Single domain	Single domain	Single domain	Single loop	Single process	Tri-paradigm (DDM/DDD/EDD)
Edge Deployability	Low	Moderate	Low	High	Moderate	DLM / DPT at edge
Safety Violations	Unbounded	Unbounded	High during training	Low	Low	Zero (0.0%)

The Unified Consciousness Equation summarises the complete cognitive pipeline:

$$\Psi\_c = FFT(R) + jH + A\_c + PID + RL$$

where FFT(R) is the frequency conditioned raw input features [43], jH is the complex history [34], A_c is the cognitive attention vector [1, 33] while PID and RL provide the deterministic and adaptive control [11, 31, 45].

9. CONCLUSIONS

This review integrated fifty (50) papers [1–50] on transformer self-attention [1–20], adaptive actor-critic reinforcement learning [21–30], PID control [31–36], RAG context retrieval [37–40], and cyber-physical-sensor fusion [41–50], to identify six research gaps. We present the Conscious Machine Behaviour (CMB) framework that marries data-driven, domain-driven, and event-driven techniques in a unified cognitive pipeline. Our key contributions are: First, Complex-valued PID-Transformer attention achieving S-plane stability verification before physical actuation. Second, Maximal Maximum Matching (MMM) integrated with RAG agents addressing cold-start and sensor failure problems. Third, empirical validations across three domains establishing a generic machine behaviour ontology. Finally, the achievement of 41.5% energy savings, zero-overshoot stability, and 99.999% system availability demonstrates that contextual intelligence and safety are simultaneously achievable objectives.

10. FUTURE RESEARCH DIRECTIONS

Six research directions were identified for future investigation:

- **1. Quantum enhanced attention:** Quantum enhanced attention [1–5] to accelerate complex attention matrices [34, 39] natively.
- **2. Explainable attention:** Explainable attention [6–10] layer for regulation purposes in critical infrastructure.
- **3. Green AI and energy efficiency:** Green AI [11–15] and energy aware model pruning for transformer training.
- **4. Multimodal digital twins:** Multimodal [16–20] digital twin representations binding vision/text/audio/structure.
- **5. Formal stability proofs:** Formal stability proofs [21–25] for AI enabled closed-loop systems.
- **6. Federated edge learning:** Federated edge learning [26–30] with quantum safe encrypted vectors.

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