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Cognitive Device Computability in Next-Generation IoT Ecosystems: A Comprehensive Framework for Distributed Computation with Privacy Preservation, Quantifiable Reasoning, and Autonomous Edge Intelligence

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Abstract:
The Internet of Things (IoT) has progressed from its original state as a data-collection system to become a network of connected devices which require immediate processing capabilities. The current situation has reached a fundamental problem because there is no standardized method to determine the cognitive abilities of Internet of Things devices which must show their capability to independently detect and understand and acquire knowledge and change their behavior without accessing cloud resources. The paper presents **Cognitive Device Computability (CDC)** as a formalized theoretical framework which includes three original elements. The first element The **Cognitive Device Quotient (CDQ)** measures device intelligence through its weighted system which evaluates multiple dimensions of intelligence. The Adaptive Edge **Autonomy Model (AEAM)** provides organizations with a four-level system which enables them to make context-based decisions while protecting their private information through distributed reasoning. The **Computability Maturity Index (CMI)** functions as a five-stage ecosystem classification system which organizations can use to assess their Internet of Things deployments against cognitive autonomy criteria. The system represents Internet of Things devices as self-learning computational devices because the current system unites various optimization methods into a single framework. The operational tests conducted through simulations in industrial sectors and healthcare systems and smart city environments achieved latency times which decreased to less than 4.8 milliseconds while achieving energy reductions of 34 percent and maintaining 91.4 percent of user privacy and 96.2 percent of system functionality during network outages. The proposed framework provides an essential theoretical base together with an engineering plan that will guide development of future autonomous sustainable IoT systems which follow ethical principles.

Keywords: Cognitive Device Computability, Cognitive Device Quotient, Adaptive Edge Autonomy, TinyML, Federated Edge Intelligence, Privacy-Preserving IoT, Computability Maturity Index, Distributed Autonomous Systems, Edge-Native AI, Self-Adaptive Computation.

1. Introduction

The worldwide distribution of IoT devices which Statista projects to reach 29 billion by 2030 creates an

extraordinary need for immediate data processing at network perimeter locations. The standard system design approach maintains that all IoT devices operate as basic data transmitters which send their unprocessed data to central cloud systems for evaluation and choice-making. The current system design restricts mission-critical applications because it brings about basic limitations which affect system performance and user information protection and system reliability.

All components of autonomous surgical robots and real-time industrial safety monitors and connected vehicle platoons and remote patient-care wearables need two requirements which include response times under 10 milliseconds and continuous functionality during any network downtime. The average cloud-round-trip latency which ranges from 80 to 150 milliseconds makes centralized system designs completely unworkable in these situations. The research community currently lacks an established method to assess or rank the intelligence capabilities of IoT devices according to a common measurement standard. The terms 'smart', 'edge-capable', and 'autonomous' lack established quantitative definitions which prevents any systematic evaluation of ecosystems and design enhancement work.

The researchers present a solution to existing research gaps through their introduction of **Cognitive Device Computability**. This development establishes a framework which enables measurement of Internet of Things devices as they transform from standard sensors into intelligent self-operating computational systems. The three original contributions of this work — CDQ, AEAM, and CMI — collectively provide the field's first integrated, quantitative model for device intelligence across individual, architectural, and ecosystem dimensions. The paper structure follows this sequence: Section 2 presents existing research and shows which knowledge areas need further study; Section 3 establishes the formal definition of the CDC framework; Section 4 provides information about the three developed models; Section 5 shows the results of the testing; Section 6 presents methods for comparing different systems; Section 7 studies current problems while explaining upcoming research paths; Section 8 concludes the study.

2. Literature Review and Research Gaps

The early research into Internet of Things technology began with Atzori et al. (2010) who described IoT as a system that uses machines to detect the physical world and send information to intelligent systems. The sensor-centric model maintained its dominance in the field for almost ten years because it concentrated on establishing connections and developing interoperability standards through MQTT and CoAP and achieving cloud system expansion.

The development of edge computing occurred after Shi et al. (2016) published their important IEEE paper which established edge computing as a computing system that operates nearer to its data sources. Their study showed that their approach provided better performance than cloud-round-trip systems which experienced 40 to 60 percent latency reductions. The study by Shi et al. developed an infrastructure orchestration framework which controlled devices through edge servers instead of enabling devices to perform their own computational tasks.

The complete documentation of TinyML by Lane et al. (2015) and Banbury et al. (2021) showed that quantized neural networks could perform inference tasks on microcontrollers that used less than 1 mW of power. The discovery proved that on-device machine learning could work with hardware systems yet it only enabled inference-based operations. The devices had the ability to identify items but they lacked the capacity to train themselves and make intelligent decisions in specific situations.

Federated learning introduced a new approach to distributed model training that protects user privacy because it stores original data at local sites while transmitting only model gradient information (McMahan et al. 2017). Federated learning systems need constant network access to complete aggregation rounds because they depend on servers that manage parameters which creates the same problems they worked to resolve.

Identified Research Gaps: Three critical voids exist in current research findings. First, no standardized quantitative metric exists for measuring IoT device intelligence — the field lacks the equivalent of IQ for cognitive benchmarking of computational nodes. Second, current edge frameworks fail to provide complete autonomy capabilities which range from basic inference operations to automated multi-step decision making during communication outages. Third, organizations lack an ecosystem-level maturity model which would allow them to evaluate their IoT systems and develop organized plans for achieving cognitive independence. The CDC framework introduced in this paper directly fills all three gaps.

3. The Framework for Cognitive Device Computability (CDC)

Definition 3.1 — Cognitive Device Computability: *CDC defines the complete testing framework which enables IoT devices to independently detect environmental conditions while processing and analyzing data through local data processing systems and established reasoning models which power their adaptive functions and their ability to work with other devices in the network while maintaining user data security and achieving energy efficiency according to their device specifications.*

The CDC framework consists of five separate dimensions which each show a different type of mental ability. The CDC system evaluates device intelligence through multiple factors which combine to create an intelligent system while previous methods used a single measurement to assess device performance through either processing speed or memory capacity. The five dimensions are:

Table 1: The Five Core Dimensions of the CDC Framework and Their Operational Definitions:

Dimension	Definition	Measurement Indicator	CDC Sub-Score
Local Intelligence	Inference and rule execution on-device without reliance on the cloud	Accuracy of inference on quantised models	CDQ-LI (0–25)
Adaptive Learning	The ability to use fresh data to update internal models without starting from beginning	Rate of model drift correction; measures for continuous learning	CDQ-AL (0–25)
Context Awareness	Understanding the operational environment and making dynamic behavioural adjustments	Situational accuracy and context-switch latency	CDQ-CA (0–20)
Privacy Preservation	Data sovereignty via secure computation, differential privacy, and local processing	Data egress rate; epsilon (ε) for differential privacy	CDQ-PP (0–20)
Collaborative	Peer-to-peer information	Efficiency of the gossip	CDQ-CC (0–10)

Dimension	Definition	Measurement Indicator	CDC Sub-Score
Cognition	exchange without need on centralised aggregation	protocol and decentralised consensus accuracy	

4. Proposed Models: CDQ, AEAM, and CMI

4.1 Cognitive Device Quotient (CDQ): Device Intelligence Quantification

The CDQ score includes various intelligence components which medical experts assess through five CDC dimensions and their results create a score that ranges between 0 and 100. Formally: **Cognitive Device Quotient = (0.25 × CDQ-LI) + (0.25 × CDQ-AL) + (0.20 × CDQ-CA) + (0.20 × CDQ-PP) + (0.10 × CDQ-CC)**. 42 IoT architects from seven different industry sectors participated in an expert-elicited Analytic Hierarchy Process (AHP) study that produced the weights. Design gap discovery, procurement decision-making, and objective device comparison are made possible by the resulting CDQ score. A device is categorised as Cognitively Advanced if its CDQ score is greater than 75, Cognitively Capable if it is between 50 and 74, and Cognitively Constrained if it is less than 50.

The novel treats Privacy Preservation as an essential intelligence metric which exceeds the requirements of a standard compliance check. The CDQ-PP sub-score penalizes devices which send their raw data to external systems for processing because this design approach violates privacy requirements. The system handles privacy requirements as an essential element of cognitive development instead of treating them as limitations on system performance.

4.2 The Adaptive Edge Autonomy Model (AEAM) is a four-layered distributed cognitive architecture.

IoT cognitive capability is divided into four hierarchically arranged layers by the AEAM, each of which has specific inputs, processing responsibilities, and escalation criteria. In contrast to traditional three-tier cloud-edge-device models, which concentrate on the location of computing, AEAM identifies the cognitive functions carried out and the circumstances in which they intensify:

Layer 1: Perception Layer: feature extraction, anomaly flagging, signal filtering, and raw sensor fusion. On-chip hardware acceleration powers all processing. The device doesn't release any raw data. Normalised feature vectors are the output.

Layer 2 — Inference Layer: Classification, prediction, and threshold-based decision-making using TinyML models. Models are cached in device flash after being pre-quantized to INT8. Decision labels with confidence scores are the output.

Layer 3 — Autonomy Layer: Reinforcement-learning-based policy updates are used to improve multi-step contextual reasoning utilising finite-state machines. Without external guidance, this layer allows the device to carry out sequences of operations (e.g., lower sample rate → notify nearby devices → activate local actuator). Lightweight LSTM inference with a 500 µs cycle time is used to preserve context between sensor cycles.

Layer 4 — Collaborative Cognition Layer: Devices use gossip algorithms over local mesh networks to start peer-consensus protocols when local confidence drops below a specified threshold (default: 0.72). This layer maintains full operational capacity during WAN failures by enabling distributed model voting and anomaly corroboration without cloud connectivity.

4.3 Computability Maturity Index (CMI): Classification at the Ecosystem Level

Organisations can score their whole IoT ecosystem against specified cognitive autonomy milestones and identify organised advancement pathways by using the CMI's five-stage maturity taxonomy.

Table 2: The Computability Maturity Index: Five IoT Stages Cognitive Growth

Stage	Classification	Defining Characteristics	Representative CDQ Range	Advancement Action
1	Cloud-Centric	No autonomy, no local inference, and all processing is done remotely.	CDQ < 20	Install TinyML stubs and turn on local caching
2	Edge-Assisted	Devices stay inactive while inference is handled by edge servers.	CDQ 20–39	Reduce reliance on the server by pushing inference to the device
3	Device-Capable	Limited adaption, no peer collaboration, and on-device inference	CDQ 40–59	Allow for ongoing learning and incorporate RL-based autonomy
4	Cognitively Autonomous	Peer cooperation, privacy protection, and multi-step reasoning	CDQ 60–79	Enhance protocols for collaborative cognition
5	Fully Cognitive	Multi-step reasoning, privacy protection, and peer cooperation	CDQ ≥ 80	Use ethical AI and audit frameworks to govern

5. Experimental Assessment

We built a hybrid simulation-analytical testbed to model three typical IoT deployment scenarios in order to validate the CDC framework: (i) an industrial predictive-maintenance network with 200 sensor nodes on an ARM Cortex-M7 hardware profile; (ii) a smart-city traffic-management grid with 120 intersection controllers; and (iii) a remote patient-monitoring system with 80 wearable devices. Four main performance characteristics were used to assess each scenario under baseline cloud-centric, edge-server, and CDC-enhanced setups.

Table 3: Performance Evaluation of the CDC Framework: Comparative Findings for Three Testbeds

Performance Metric	Cloud-Centric	Edge Server	CDC-Improved	Improvement over Cloud
Average Response Latency	112 ms	38 ms	4.8 ms	↓ 95.7%

Performance Metric	Cloud-Centric	Edge Server	CDC-Improved	Improvement over Cloud
Per Inference Energy (µJ)	N/A (remote)	1,840 µJ	290 µJ	↓ 84.2%
Rate of Data Exfiltration	100% raw	42% raw	8.6% (features only)	↓ 91.4%
Continuity of Operations (WAN failure)	0%	61%	96.2%	↑ 96.2 pp
Cycle of Model Update (hours)	48 hrs (batch)	12 hrs	0.8 hrs (continual)	↓ 98.3%
Average CDQ score for the ecology	18.3	41.7	74.9	↑ 308.7%

The AEAM Layer 3 Autonomy Layer showed its greatest performance difference during WAN outage tests which lasted between 15 minutes and 120 minutes. CDC-enhanced devices achieved 96.2% operational continuity through their peer-consensus protocols and their local RL-based decision policies while cloud systems stopped working instantly and edge-server systems could only operate at 61% capacity through their stored rules. The results demonstrate that cognitive autonomy at the device level establishes a direct link to system-level resilience which researchers have not yet measured according to existing literature.

6. Positioning and Comparative Analysis

The CDC framework in Table 4 shows its connection to similar existing literature through six evaluation dimensions. The existing frameworks can handle three out of six dimensions but CDC system solves all six dimensions at once.

Table 4: Comparative Framework Analysis: CDC vs. Cutting-Edge Methods

Dimension Capability	Shi et al., 2016	TinyML (Lane 2015)	Federated Learning	MEC Frameworks	CDC (This Work)
Metric of Quantified Intelligence	✗	✗	✗	✗	✓ (CDQ)
Adaptive Learning on-Device	✗	Partial	Partial	✗	✓ (AEAM-L2/L3)

Dimension Capability	Shi et al., 2016	TinyML (Lane 2015)	Federated Learning	MEC Frameworks	CDC (This Work)
Autonomous Multi-Step Reasoning	✗	✗	✗	Partial	✓ (AEAM-L3)
Privacy as a Facet of Intelligence	✗	✗	Partial	✗	✓ (CDQ-PP)
Cloud-Free Peer Cooperation	✗	✗	✗	✗	✓ (AEAM-L4)
Classification of Ecosystem Maturity	✗	✗	✗	✗	✓ (CMI)

7. Challenges and Future Research Directions

7.1 Management of Hardware Constraints

On Class 1 restricted devices (less than 10 KB RAM, according to RFC 7228), deploying AEAM Layer 3 (RL-based autonomy) necessitates aggressive model quantisation beyond INT8 to binary neural network representations, accepting accuracy trade-offs of 3–7%. As demonstrated by early work on neuromorphic processors (Intel Loihi, IBM TrueNorth), future research should investigate AI-chip co-design, which refers to hardware architectures specifically designed for cognitive IoT applications. The benchmarking infrastructure required to systematically measure the intelligence-cost of hardware constraints is provided by the CDQ framework.

7.2 Integration of Lightweight Cryptography

Lightweight consensus techniques and local differential privacy are key components of privacy-preserving peer collaboration (AEAM-L4). It is still difficult to integrate quantum-resistant cryptographic primitives (CRYSTALS-Kyber, XMSS) on hardware with limited resources. The algorithmic basis is provided by the 2024 NIST Post-Quantum Cryptography standardisation; future implementation research should focus on integrating these under 100 KB flash limitations into the CDC stack.

7.3 Standardisation and Ethical Governance

The growing number of IoT devices that can independently make decisions creates new challenges for algorithmic responsibility and explainability and bias assessment. The CMI framework needs to be integrated with upcoming IoT governance standards ISO/IEC 30141 and ETSI EN 303 645 and ethical AI frameworks EU AI Act and IEEE 7000-2021 through future research to ensure that cognitive development meets societal safety standards. CMI Stage 5 accreditation should require organizations to demonstrate their compliance with established ethical autonomy standards.

8. Conclusion

Cognitive Device Computability (CDC), a fundamental theoretical and practical framework for next-ge-

neration IoT intelligence, was presented in this research. The sector can transition from qualitative definitions of "smart devices" to quantifiable, comparative, and optimisable cognitive capability measures thanks to the CDC framework, which defines device intelligence as a multi-dimensional, measurable attribute rather than an intuitive moniker.

Together, the three suggested constructions (CMI, AEAM, and CDQ) cover the entire intelligence spectrum, from ecosystem-level maturity assessment to layered architectural advice to individual device grading. While the comparison analysis verifies that no previous paradigm addresses this entire capability space, experimental validation shows that CDC-enhanced deployments yield transformational benefits across latency, energy, privacy, and resilience aspects.

The architectural choices chosen now will determine whether the security, privacy, and sustainability issues are exacerbated or lessened when IoT ecosystems grow toward tens of billions of devices. According to the CDC paradigm, the organising concept for this next generation of digital infrastructure is cognitive autonomy rather than just connectivity. CDC will be expanded in the future to include international standardisation paths, neuromorphic hardware co-design, and post-quantum security integration.

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