JA x Deloitte.

Driving the Greening of Artificial Intelligence through GTI White Paper

(Green Token Index, GTI)

GTI

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Contents

Executive Summary

Artificial intelligence (AI) is emerging as a foundational layer of next-generation global infrastructure. However, as large-scale model training and inference continue to scale, the rapid expansion of computational demand is placing growing pressure on energy systems, making sustainability an increasingly critical issue in the future evolution of AI.

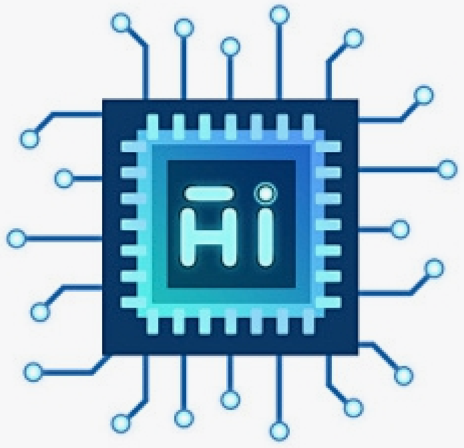
Current approaches to green computing—including renewable electricity procurement, energy-efficiency optimization, and carbon offset mechanisms—have improved aspects of energy structure and operational efficiency. However, the industry still lacks a unified foundational framework capable of consistently measuring and expressing the sustainability attributes of AI computational activities.

Against this backdrop, the Green Token Index (GTI) proposes, for the first time, the introduction of sustainability attributes into the fundamental units of AI computation.

GTI represents a conceptual transition from “green electricity” toward “green computation”, enabling the environmental value associated with AI systems to become measurable, comparable, and potentially standardizable.

More fundamentally, GTI seeks to establish a shared language connecting computational systems, energy systems, and sustainability value frameworks, enabling sustainability attributes to be systematically integrated into AI infrastructure frameworks and discussions.

Key Insights



01. Green attributes should become a core dimension of AI infrastructure. The future of AI competition will no longer be defined by computational efficiency alone, but by the combined strength of performance and sustainability.

02. As the fundamental unit of computation in AI systems, the Token can serve as a critical link between computing power consumption and the corresponding energy attributes.

03. By directly anchoring each Token to the share of green energy used in its generation, GTI embeds sustainability into the computing process itself. This enables, for the first time, a standardized framework for quantifying and comparing the environmental impact of diverse AI workloads.

04. GTI may further evolve into an interface for broader value systems, connecting certification mechanisms, environmental rights, and collaborative green ecosystems.

Proposed Initiatives

01

Advance the exploration of GTI as a foundational measurement framework, and build industry consensus around the definition and measurement scope of green attributes.

02

Launch pilot programs and certification mechanisms to support GTI implementation.

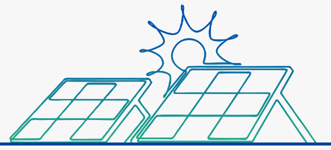
03

Promote coordinated governance between energy systems and computing infrastructure by integrating green energy supply, computational scheduling, and sustainability objectives into a unified system framework, thereby enabling the practical deployment of Green AI infrastructure.

The Structural Tension Between AI and Energy

For years, computing power and energy systems were rarely discussed within a unified strategic framework. Early AI development was primarily constrained by algorithmic breakthroughs and improvements in computational capability. Model sizes remained relatively limited, while energy costs represented only a modest share of overall data center investment. As a result, industry attention to energy constraints largely remained at the level of basic operational support rather than strategic concern. The deployment of computing infrastructure was therefore driven mainly by considerations such as network connectivity, land availability, and hardware resources, with green energy rarely treated as a core factor.

This landscape began to shift with the rise of large-scale foundation models and generative AI. The rapid expansion of model parameters, longer training cycles, and increasingly frequent inference requests have transformed Token consumption and computational workloads from episodic growth into sustained expansion. As a result, AI infrastructure is becoming increasingly energy-intensive, as data center electricity demand continues to rise. AI has now emerged as a significant new source of electricity demand.



Data Center Power Demand Will SurgeOver the Next Decade, Driven by AI

Historical Data and Forecast of Data Center Electricity Demand (2010-2035)

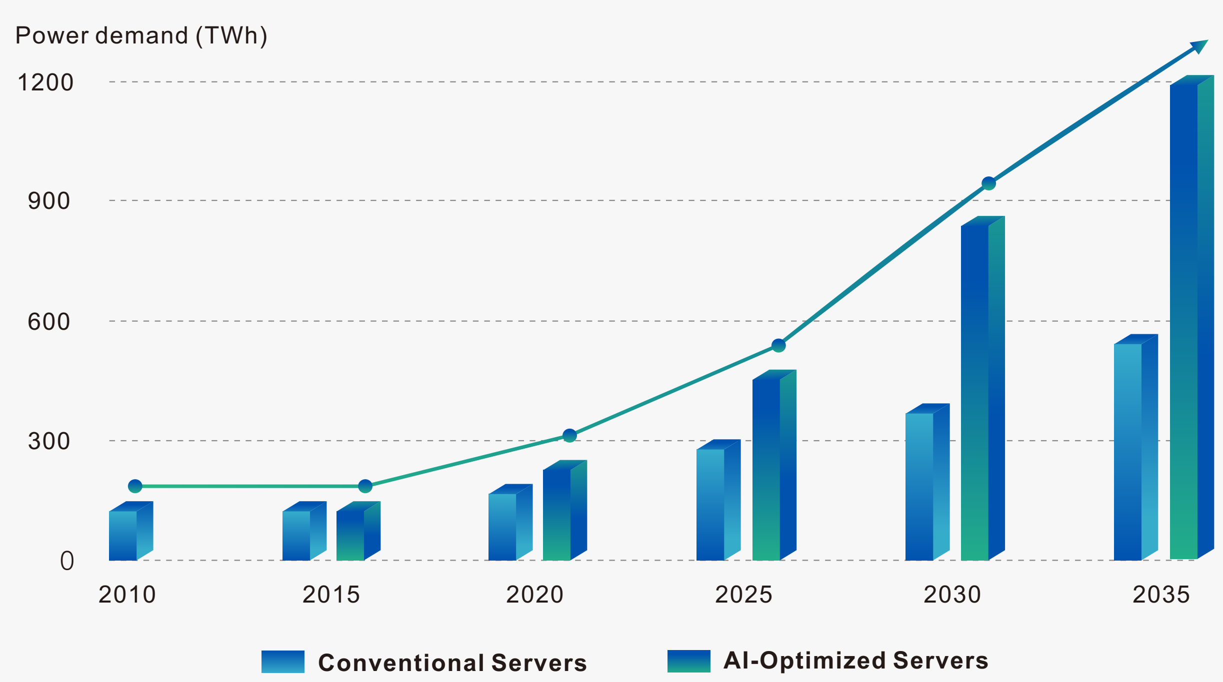
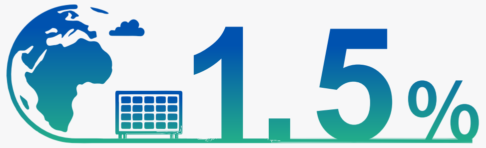


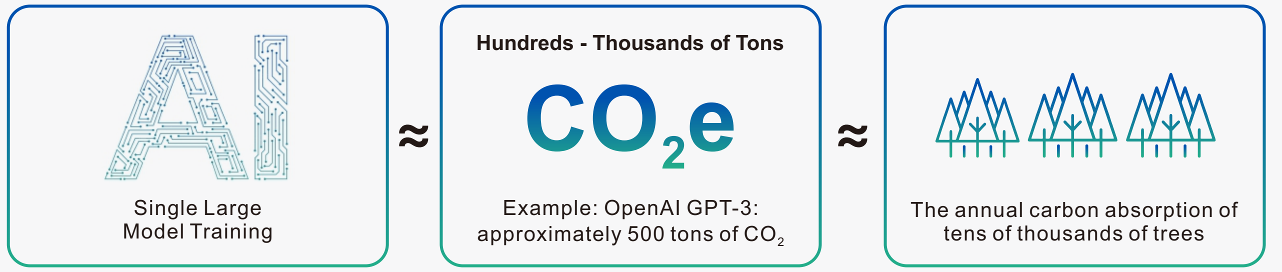
Figure 1: Energy consumption and emissions associated with AI development

Source: International Energy Agency (IEA)



Currently, global data center electricity consumption accounts for approximately **1.5%** of global electricity demand and is expected to nearly double before 2030. Carbon emissions from training a single large model have reached kiloton-scale CO_2 emissions , which is comparable to the annual carbon absorption capacity of tens of thousands of trees.

Under this trend, without effective constraints and structural optimization, the future AI infrastructure expansion will directly correspond to larger-scale data center construction and energy consumption, exerting sustained pressure on power systems and carbon emission systems.



Note: Based on carbon emissions of hundreds to thousands of tons CO_2e per single large model training, a single tree absorbs approximately 4-18.3 kg CO_2 per year

Figure 2: Schematic Diagram of Energy and Carbon Emission Levels for AI Computing

More importantly, this shift is not reflected merely in the growth of total energy demand. It exposes a deeper structural disconnect between computational systems and energy systems. Despite the continued expansion of renewable energy supply, AI computational activities and energy systems have not yet been effectively coordinated. Instead, multiple forms of misalignment are becoming increasingly evident:

- **Temporal mismatch:** Renewable energy sources such as wind and solar are inherently variable, while AI computational demand is continuous and stable
- **Spatial mismatch:** Renewable energy resources are concentrated in specific regions, whereas computational demand is concentrated in data- and application-intensive regions
- **System-level mismatch:** Energy systems and computational systems have evolved largely in parallel, lacking unified coordination mechanisms

In this context, the continued growth of green energy supply does not necessarily translate into effective alignment with AI computation. In practice, the extent to which green energy is matched to AI workloads remains limited. At the same time, existing mechanisms—including renewable electricity procurement, renewable energy certificates, and carbon offsetting—remain largely focused on the energy side or end-result accounting, making it difficult to establish a direct mapping between AI computational activities and their green attributes.

As AI increasingly becomes a new generation of foundational infrastructure, energy is shifting from a peripheral constraint to a structural issue. Against this backdrop, introducing measurable and expressible green attributes into AI systems becomes a practical starting point for further discussions on the development pathway of Green AI.

Green AI as a New Development Paradigm for Intelligent Infrastructure

Discussions surrounding the future of AI are extending beyond capability growth itself toward how the sustainability of that growth can be achieved. Against this backdrop, Green AI has emerged as a new paradigm. Its purpose is not to place constraints on the development of intelligent capabilities, but to embed green attributes as a foundational value dimension throughout the process of technological evolution.

This direction implies that the goals of AI development can no longer be defined solely by model performance or lower inference costs. They must also account for the coordination among resource efficiency, energy sources, and environmental impact. Under this framework, “green” is beginning to shift from an external constraint to an intrinsic attribute of intelligent systems.

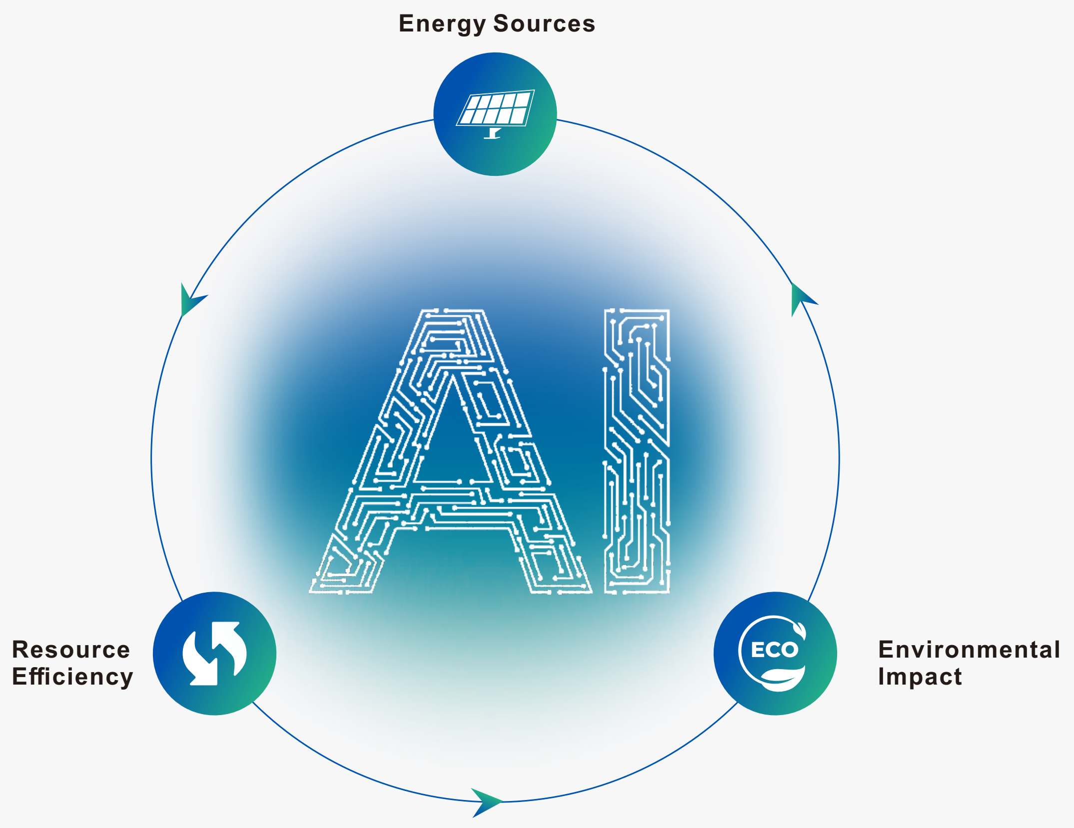


Figure 3: Relationship between AI, Resource Efficiency, Energy Sources, and Environmental Impact

As the understanding gradually takes shape, green AI is no longer merely a discussion about optimizing energy use. Instead, it has begun to evolve into a directional initiative for the future evolution of intelligent infrastructure. The next critical question, therefore, is how these green attributes can be concretely articulated and transformed into evaluable objects.

GTI: Establishing a Foundational Framework for Green AI Measurement

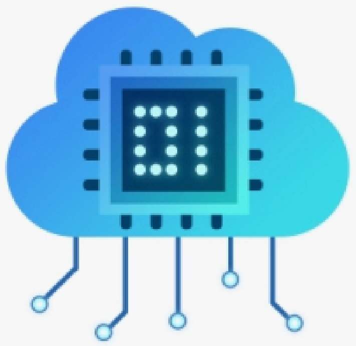
For green attributes to become an evaluable dimension within AI systems, they must be supported by an appropriate measurement carrier—one that allows them to be identified, compared, and expressed in a unified way. GTI is not a new digital asset, nor is it a crypto Token in the traditional sense. Rather, it is a foundational measurement unit designed to describe the green attributes of AI computational activities. It represents the level of green energy coverage associated with the generation of a unit of AI Token, reflecting the relationship between AI computational activities and green energy. Under this framework, the Token is no longer merely a unit of AI computation and service delivery; it also gains the ability to express energy and environmental attributes, thereby becoming an important foundational carrier that connects AI computing systems with green energy systems.

Within existing AI systems, compared with lower-level technical metrics such as device performance parameters, GPU hours, or FLOPs, the Token serves both as a basic unit of computation in training and inference, and as an important unit for expressing AI service delivery and resource consumption. It therefore naturally connects the technical infrastructure layer with the application layer.

Traditional Tokens describe computational activity itself, but they do not express the energy source or environmental attributes behind that activity. The introduction of GTI builds on this logic by incorporating green attributes into Token measurement, expanding the Token from a single-purpose compute unit into a measurement carrier that reflects both computational value and green value. This means that the evaluation of AI computational activities will no longer focus only on how many Tokens are generated, but also on the green attributes associated with those Tokens. In this way, Green AI begins to acquire the foundational conditions needed to move from a development initiative toward a framework that can be evaluated, compared, and potentially standardized.

More broadly, the significance of GTI may lie not only in providing a new method for green measurement, but also in establishing a unified language of value expression between AI computing systems and energy systems. This would allow green attributes to enter AI infrastructure systems in a unified way for the first time. From a longer-term perspective, GTI may further evolve into an important interface connecting computing power, energy, and environmental value systems, providing a new foundational language for the future coordination of Green AI infrastructure, green computing governance, and environmental value mapping systems.

GTI Measurement Methodology and Pathway Options



Following the introduction of the GTI concept, the discussion naturally shifts toward a more practical question: how can sustainability attributes be measured in a stable and credible manner?

Without a unified and executable measurement framework, sustainability attributes cannot effectively evolve from conceptual discussion into a system that is comparable, verifiable, and usable in practice.

At the current stage, the core issue surrounding GTI is not merely how to describe green attributes, but how to establish a foundational methodology capable of balancing authenticity, standardization, and scalability.

Using the Share of Green Energy in AI Token Computation as the Core Metric

As a measurement vehicle, GTI requires a clear and quantifiable underlying indicator. The proportion of green energy contained within the electricity consumed during AI Token generation may serve as this foundational metric.

Compared with metrics such as device-level efficiency, carbon emissions per task, or lower-level computational parameters, this indicator directly reflects the underlying energy source itself and therefore provides a clearer representation of the energy structure supporting AI computational activities.

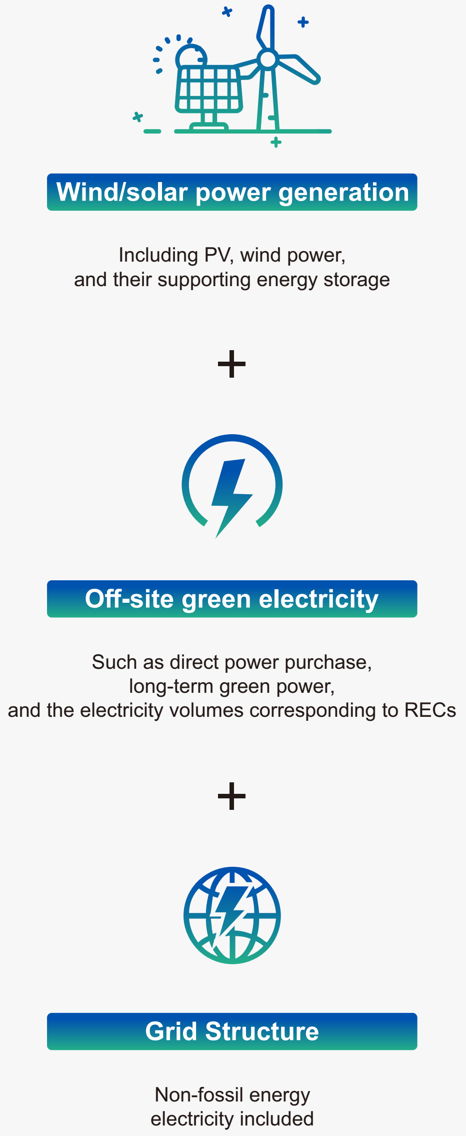
At the same time, the metric is highly extensible. It can potentially be linked to renewable energy certificates, carbon assets, and future environmental rights frameworks, allowing GTI to evolve beyond a measurement unit into a broader interface connected to environmental value systems.

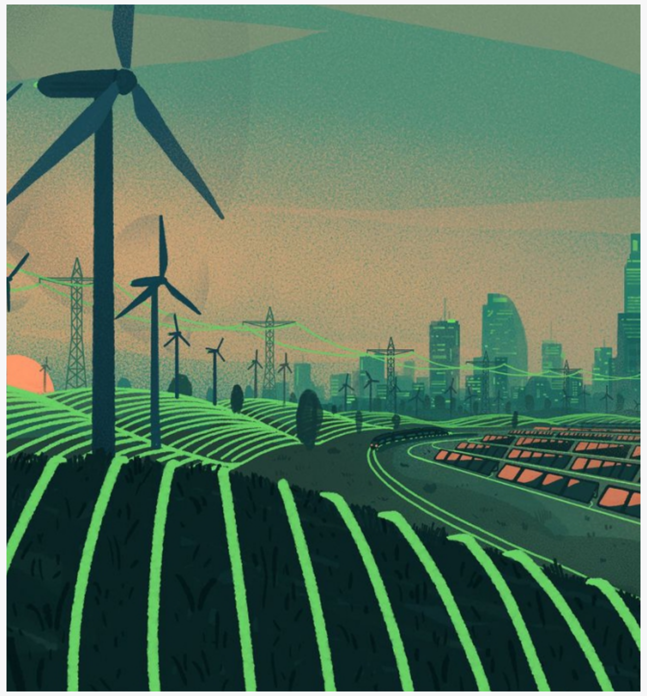
Under this framework, the key question becomes: how can such a metric be calculated consistently and credibly under complex energy structures and distributed computational scheduling environments?

Defining the Boundaries and Accounting Standards of Green Electricity

Before designing a measurement methodology, the scope and accounting standards of green electricity must first be clearly defined.

In practice, electricity consumed by data centers is typically sourced through multiple channels, and its sustainability attributes cannot be adequately represented by a single energy category.





It should be noted that different sources of green electricity vary in terms of traceability and temporal matching. On-site wind and solar generation can be directly linked to electricity consumption at the physical level, while externally procured green electricity and grid-based green electricity rely, to varying degrees, on statistical allocation or contractual attribution.

Accordingly, different sources of green electricity need to be treated differently in the measurement process, in order to avoid overstating or distorting green attributes in accounting. This principle is not intended to draw a simplistic distinction between the value of different energy sources. Rather, it is designed to reflect the actual structure of energy use as closely as possible within a unified framework, thereby enhancing the credibility of the attributes expressed by GTI.

Comparing Two Measurement Approaches: Dynamic Time-Slice Accounting vs. Full-Scope Aggregate Accounting

Once the indicator and accounting boundaries are established, GTI measurement methodologies can broadly be divided into two primary approaches.

1. Dynamic Time-Slice Accounting

This methodology uses time as the core dimension by matching renewable energy supply with computational workloads under unified temporal intervals. Through real-time or near-real-time accounting, it captures the actual utilization of green energy across different time periods.

Its significance lies not only in improving measurement precision, but also in establishing a time-correlated authenticity relationship between renewable energy availability and AI computational activities.

2. Full-Scope Aggregate Accounting

Under this framework, sustainability attributes are calculated over a defined accounting cycle by measuring the relationship between total renewable energy consumption and total electricity usage associated with AI computational activities.

Rather than emphasizing real-time granularity, this approach focuses on overall system-level accounting consistency and unified attribution.

Although both methodologies are capable of describing green attributes, they differ significantly in terms of applicability, scalability, and standardization objectives.

Dimension	Dynamic Time-Slice Accounting Method	Full-Scope Aggregate Accounting Method
Theoretical authenticity	High real-time granularity	More stable periodic characteristics
Complexity of data collection	High implementation barrier	Relatively controllable and easily deployable within EMS
Verifiability	Difficult, with complex verification under cross-node scheduling	Aligned with the logic of existing energy statistics, ESG disclosure, and renewable electricity certification systems
Uniformity of standardization	Prone to fragmentation	Easily unified in measurement scope
Scalability and industrial adaptability	Currently limited	Applicable to single-site, multi-site, and cross-regional complex scenarios
Institutional compatibility	Technically oriented	Compatible with existing systems

Table 1: The comparison of two different measurement approaches

Selecting Full-Scope Aggregate Accounting as the Foundational Path at the Current Stage

These two methodologies should not be viewed as mutually exclusive alternatives. Rather, they represent different stages within the potential evolution of GTI measurement systems.
At the current stage of industry development, when standards are still at an early stage, the Full-Scope Aggregate Accounting Method is better suited as the foundational measurement pathway for GTI.
Its primary advantage does not lie in achieving absolute precision, but in balancing operational feasibility, verifiability, and scalability under real-world conditions.

This approach aligns effectively with existing frameworks for energy accounting, ESG disclosure, and renewable energy certification, thereby providing a more stable institutional foundation for sustainability attributes while reducing the risk of fragmented measurement standards caused by inconsistent data granularity.
At the same time, the Dynamic Time-Slice Accounting Method remains strategically significant.
As energy management systems, computational scheduling systems, and power-sector data transparency continue to evolve, this methodology may become an important future direction for higher-precision sustainability measurement, while preserving long-term flexibility for the GTI framework.

GTI Implementation Measures and Pathways

Following the selection of the Full-Scope Aggregate Accounting Method as the foundational pathway at the current stage, the next critical challenge for GTI is no longer the methodology itself, but how to translate measurement logic into an operational implementation framework.

The implementation of GTI is not simply the application of a formula. Rather, it is a coordinated mapping process across energy accounting systems, computational operation systems, and Token generation systems.

Its central objective is to ensure that sustainability attributes can be expressed in a stable, unified, and verifiable manner within increasingly complex AI infrastructure environments.
Meanwhile, governance and coordination interfaces must remain embedded within the framework design process in order to support the long-term credibility and evolution of GTI.

Figure 4: GTI Systematic Realization Process

Layer One:
Establishing the Foundational Green Energy Measurement System

The credibility of GTI begins with unified boundaries and accounting standards for green electricity.
At the implementation level, standardized statistical methodologies and periodic accounting rules must be established for multiple categories of renewable energy sources, including on-site renewable generation, externally procured green electricity, energy storage balancing electricity, and electricity associated with renewable certificates.

In parallel, data centers must establish unified energy accounting systems covering total renewable energy consumption, overall electricity usage, and IT load structures, thereby enabling renewable energy inputs to be systematically linked with AI computational activities.

This layer provides the foundational basis for subsequent allocation of sustainability attributes.

Meanwhile, the role of energy storage systems within sustainability accounting must also be incorporated into a unified attribution framework in order to ensure consistency and authenticity throughout the accounting process.

The primary objective at this stage is not extreme granularity, but rather the establishment of a broadly adoptable and operationally stable energy accounting foundation for the industry.

Layer Two:
Establishing a Mechanism for Mapping Computing Power to Energy Consumption

Once the foundational renewable energy accounting framework has been established, GTI must further address a second critical issue: how energy usage is mapped onto AI computational activities.

To enable sustainability attribution, unified data linkage mechanisms must be established among AI platforms, computational scheduling systems, and data center operational systems, allowing Token outputs to be associated with corresponding computational workloads and energy consumption.

Within single-site environments, sustainability attributes may be allocated based on aggregate IT load distribution.

Within cross-regional and multi-data-center scheduling environments, however, weighted attribution mechanisms become necessary. These may incorporate factors such as execution nodes, computational workload allocation, or actual energy consumption ratios.

As AI infrastructure continues to evolve, this mechanism may further integrate scheduling systems, energy management systems, and model operation parameters in order to establish dynamic sustainability attribution across the task layer, model layer, and platform layer.

Such evolution would strengthen the consistency and scalability of GTI within complex AI infrastructure ecosystems.

Layer Three:
Establishing the GTI Accounting and Identification System

After calculating renewable energy coverage ratios and completing energy-consumption mapping, GTI must further establish a unified sustainability expression mechanism.

This mechanism enables AI platforms, model services, and computational infrastructure providers to express sustainability attributes in a recognizable, comparable, and displayable manner. Its significance lies in transforming sustainability attributes from backend accounting logic into a unified language oriented toward users, enterprises, and markets.

This layer also provides a standardized interface for future rating systems, certification mechanisms, and broader industrial coordination. Relevant GTI identifiers may eventually be integrated into AI application interfaces, API documentation, model service platforms, and intelligent computing center service environments, thereby enabling transparent sustainability disclosure and market-level recognition. The broader GTI rating and visual identity framework will be further elaborated in subsequent chapters.

Layer Four:
Establishing Verification and Trust Mechanisms

If GTI is to earn lasting credibility, corporate self-disclosure alone will not be enough. It will also require a robust framework for verification, traceability, and institutional trust. At the center of this mechanism is a collaborative accounting framework involving multiple stakeholders.

AI platforms and data centers can serve as the primary providers of foundational data, periodically reporting key parameters such as renewable electricity consumption, renewable certificate attribution, and total electricity use according to unified reporting cycles.

Building on this data foundation, third-party rating alliances or verification institutions can conduct sustainability accounting, generate ratings, and validate the results.

Industry databases can further support the accumulation of baseline parameters, historical records, and sector-wide benchmarks, enabling horizontal comparability across platforms as well as long-term consistency.

To strengthen trust among multiple participants, trusted data technologies such as blockchain may be introduced to create tamper-resistant records and chronological evidence for renewable electricity consumption, certificate attribution, computational scheduling processes, and rating outcomes. Such mechanisms can significantly improve the traceability of sustainability attributes in cross-regional and multi-platform environments.

Where commercial confidentiality or user data privacy is involved, complementary mechanisms such as privacy-preserving computation, off-chain storage, and tiered authorization frameworks may also be incorporated. This would help balance collaborative verification with data security and privacy protection.

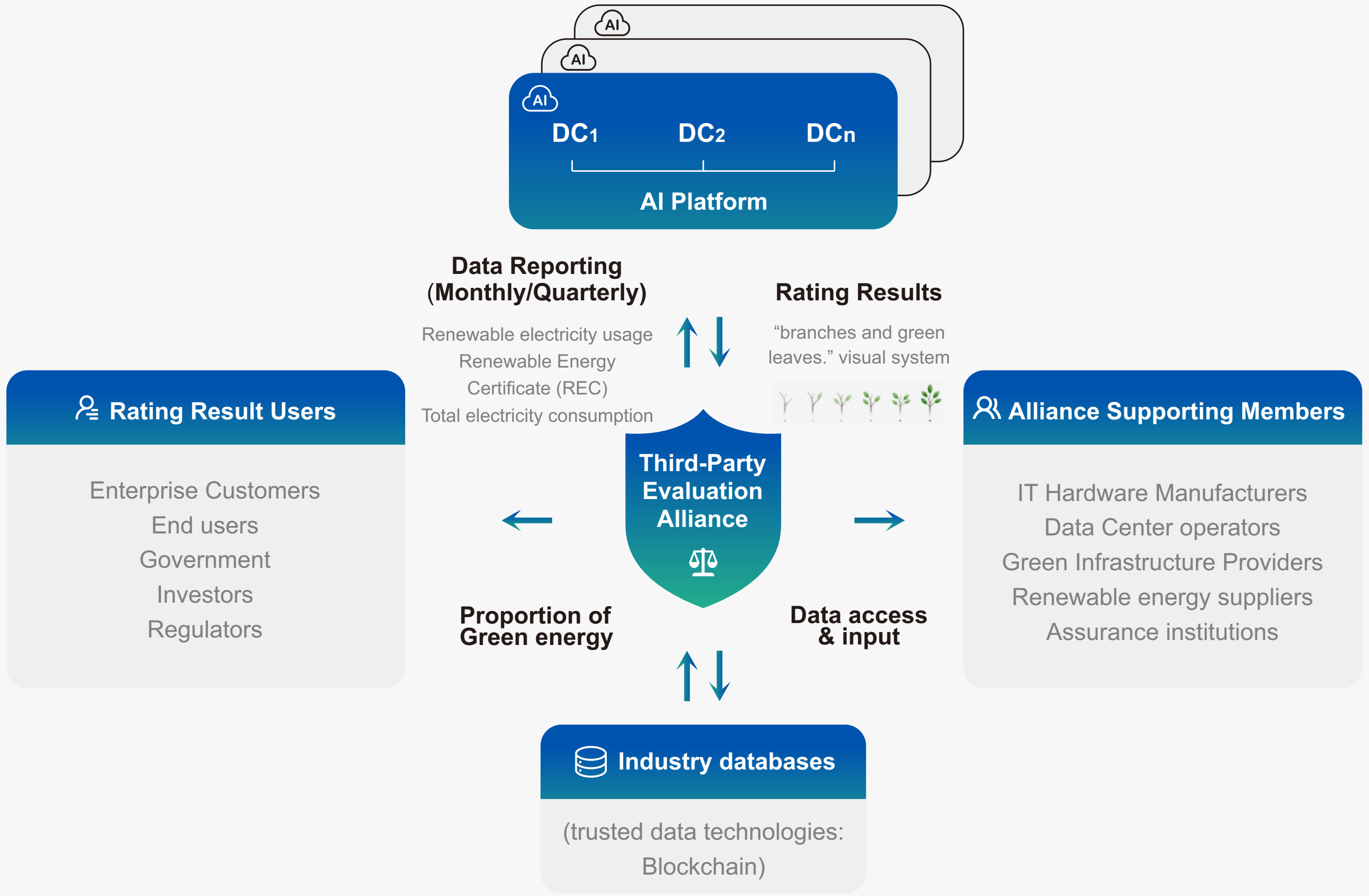
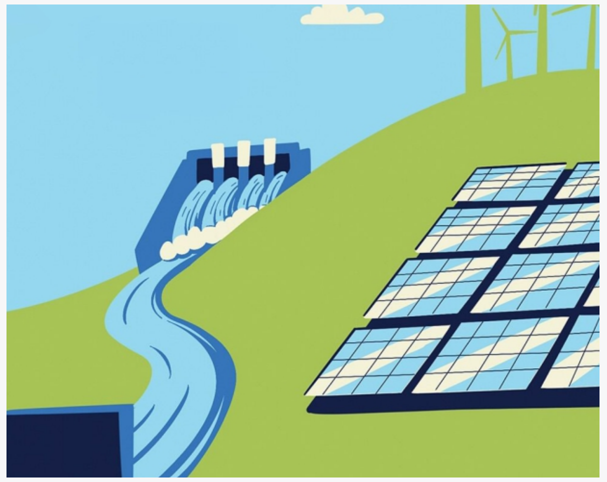


Figure 5: Schematic Diagram of GTI Collaborative Accounting and Rating Mechanism

At the same time, supporting stakeholders—including IT hardware manufacturers, data center operators, green infrastructure providers, renewable energy suppliers, and assurance bodies—may jointly contribute to standards alignment and ecosystem development.
On the application side, enterprise customers, end users, regulators, and investors may gradually become part of the value transmission process associated with sustainability attributes.
In this sense, GTI is no longer a static accounting outcome. Instead, it becomes a continuously evolving mechanism that integrates periodic reporting, trusted verification, rating generation, market feedback, and iterative rule refinement.

Layer Five: Advancing a Phased Implementation Pathway

The establishment of the GTI system is unlikely to be achieved in a single step. Rather, it is more likely to evolve gradually as the industry matures across multiple stages.
In the short term, efforts may focus on foundational accounting and pilot disclosure based on the Full-Scope Aggregate Accounting Method, with the aim of establishing a shared industry language and initial implementation practices.
In the medium term, the industry may further develop unified GTI certification rules, standardized identification systems, and cross-platform coordination mechanisms. This would allow sustainability attributes to gradually enter AI service evaluation systems and broader industrial collaboration scenarios.



From a longer-term perspective, as renewable energy systems, computational scheduling systems, and digital infrastructure governance capabilities continue to mature, GTI may evolve beyond a foundational measurement tool into an infrastructure-level framework that connects computing power, energy systems, and environmental value systems.
Through this implementation pathway, GTI moves beyond conceptual definition and begins to acquire the characteristics of a potential infrastructure-level governance framework, capable of supporting broader industrial applications and long-term social value creation.

GTI Sustainability Identity System

Building on the unified expression framework established by GTI, the framework further proposes a standardized rating and visual identity system for Green AI.
At the current stage, GTI ratings may be classified according to the proportion of renewable energy supporting AI platform operations and expressed through a unified visual structure.
The GTI visual system adopts a symbolic structure composed of “branches” and “green leaves”. Within this structure, the branches represent the foundational energy structure, while the leaves represent the degree of renewable energy coverage. As the share of renewable energy increases, the corresponding sustainability rating rises accordingly.

Figure 6: GTI Green Rating & Visual Identity System

Under the proposed framework, Level 0 indicates that renewable energy coverage has not yet reached an effective sustainability threshold, while Level 5 represents a relatively high level of renewable-energy-driven AI operational capability.
This visual system may serve as a standardized mechanism for expressing GTI sustainability identity, while also retaining the flexibility to evolve dynamically over time.

As the energy structures of AI platforms change, ratings may be updated periodically—for example, on a monthly or quarterly basis—so that sustainability attributes can continue to reflect actual changes in renewable energy usage.
Over time, these identifiers may gradually be integrated into AI service interfaces, model platforms, and intelligent computing service ecosystems, enabling unified sustainability disclosure across AI infrastructure environments. The significance of this mechanism goes beyond visual labeling alone.
More fundamentally, it introduces sustainability attributes into AI service evaluation systems for the first time. As the industry matures, sustainability may become a core dimension of AI infrastructure alongside security, stability, and performance.

Meanwhile, the unified identification framework creates future interfaces for GTI certification systems, green computing marketplaces, and environmental value coordination mechanisms.
It may also gradually be incorporated into ESG disclosure systems, green procurement frameworks, green cloud service evaluation standards, and user-facing selection mechanisms, enabling sustainability attributes to play a broader role in industrial coordination and market-based evaluation systems.

Expanding the Value Landscape of Green AI

The significance of GTI as a foundational measurement framework extends far beyond accounting methodology. It also creates new possibilities for sustainability attributes to enter application scenarios, market mechanisms, and broader systems of social value. As a result, the value proposition of Green AI begins to move beyond the purely technological domain and into a broader strategic and economic landscape.

At the industrial level, sustainability attributes may increasingly become a new reference dimension for enterprises when selecting AI services. As supply chain carbon disclosure requirements continue to intensify and ESG objectives become more deeply embedded in corporate governance, the evaluation of AI services may gradually expand beyond performance and cost to include sustainability attributes.

Under this trajectory, sustainability may evolve from a peripheral consideration into an integral component of high-quality AI services, and potentially into a new source of competitive differentiation.

At the user level, Green AI introduces a form of value perception that has long been absent from digital service consumption. For many years, users of digital services have had limited visibility into the energy structures underlying those services.

Once sustainability attributes become identifiable and transparently expressed, however, they may begin to function in user decision-making in a way similar to security, privacy, or reliability indicators. This could ultimately create market-driven momentum for the broader adoption of sustainable AI applications.

More broadly, the significance of Green AI extends beyond enterprises and end users. As an exploratory pathway connecting digital economic growth with sustainability objectives, Green AI may help shift the relationship between energy systems and computational systems from parallel development toward deeper structural coordination. In doing so, it may also contribute to the emergence of new governance paradigms for future digital infrastructure.

The logic of sustainability value may further extend into capital allocation and resource-pricing systems. Once sustainability attributes become measurable and recognizable, they may gradually enter investment evaluation frameworks, green financial products, and potentially even future asset-pricing mechanisms.

Under such conditions, Green AI would not merely represent a response to the energy challenges associated with technological evolution. It may also open up entirely new value spaces around green computing infrastructure and sustainability-linked digital economies.

GTI Energy Architecture: Toward Coordinated Renewable-Compute Infrastructure

For GTI to take shape, it requires not only measurement methodologies and verification mechanisms, but also a stable, sustainable, and dispatchable green energy system as its practical foundation. Without energy infrastructure that matches the load characteristics of AI computing, green attributes will be difficult to sustain during actual computational processes, and their assessability and verifiability will be difficult to realize in practice. Therefore, as the GTI framework extends from measurement to infrastructure, building a green energy supply system tailored to AI computing scenarios becomes a critical supporting component of the GTI system.

Compared with traditional data centers, AI-oriented data centers, or AIDCs, feature higher load density, greater continuity, and stronger real-time requirements. The rapid growth of large-model training, inference services, and AI agent applications is shifting AI infrastructure from periodic high-load operation to sustained, long-duration operation. As a result, computing systems now place significantly higher demands on power supply stability, dynamic adjustment capability, and energy coordination efficiency.

Against this backdrop, the energy solution associated with GTI is not about replacing one form of energy with another. Its core lies in building an integrated "Source–Grid–Load–Storage–Compute" green energy coordination system for AIDC scenarios. This system is based on renewable energy supply, connected by intelligent grid infrastructure, centered on AIDC computing loads as the core application scenario, supported by energy storage systems for regulation, and optimized through computing scheduling systems to coordinate the energy side and the computing side. In this way, green energy can become available, stable, dispatchable, matchable, and measurable at the same time.

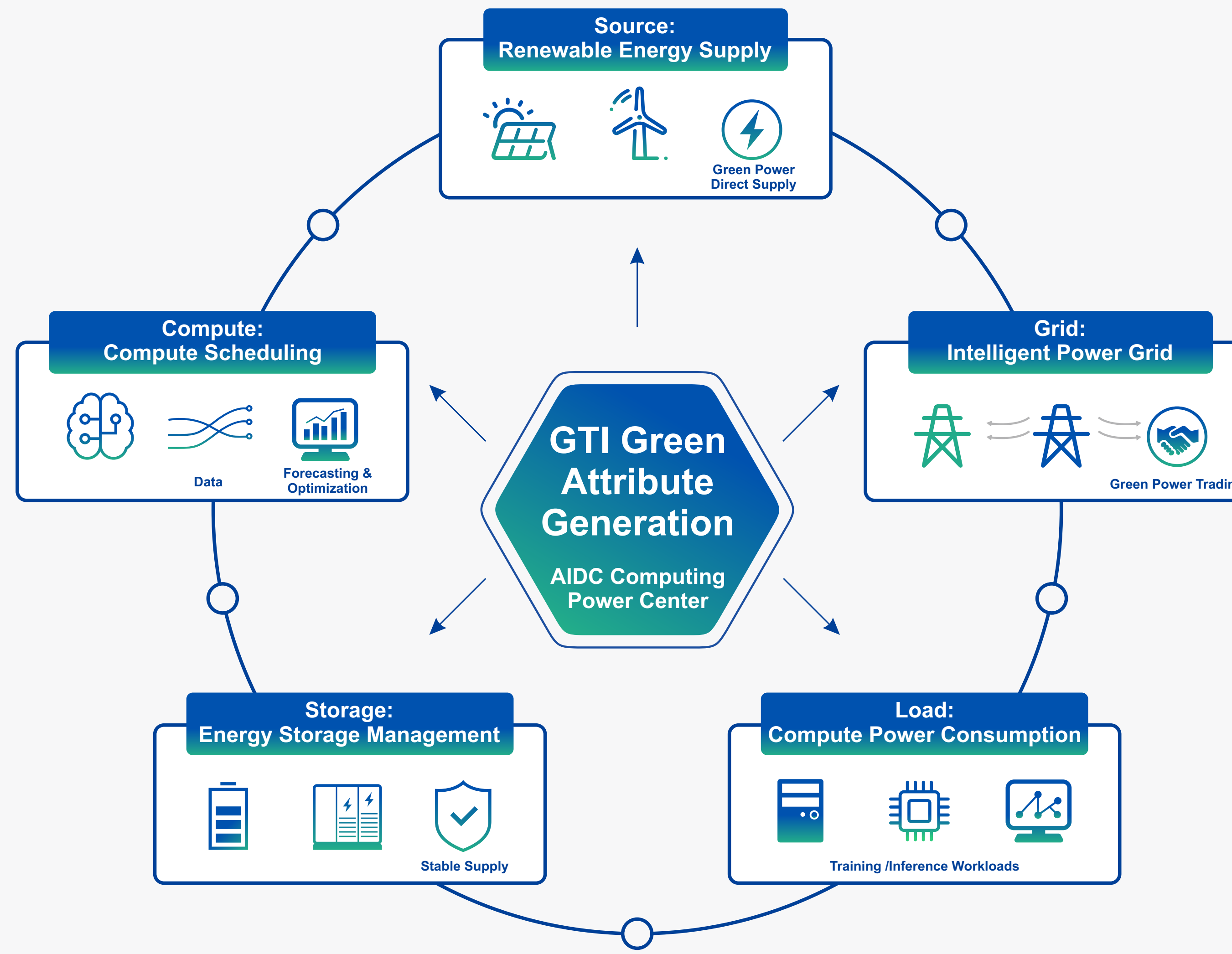
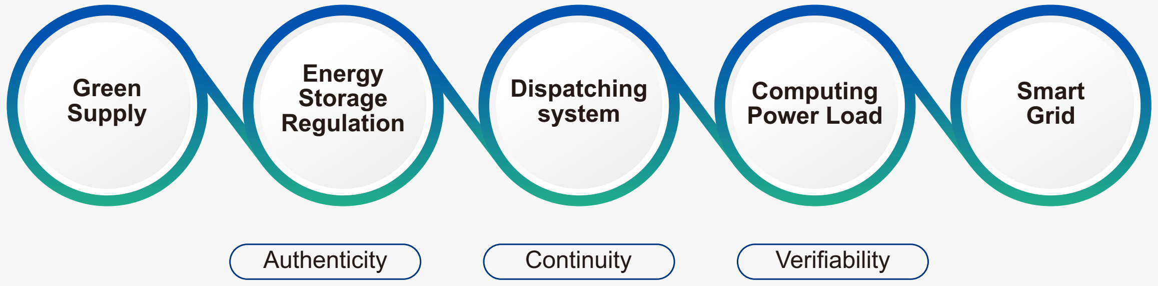


Figure 7: Coordinated "Source–Grid–Load–Storage–Compute" Green Energy System Architecture

Under this framework, the GTI energy architecture gradually forms a coordinated chain linking renewable energy supply, grid connectivity and allocation, storage-based stabilization, computational load response, and sustainability attribute generation. Renewable energy is first allocated through grid and dispatch systems, then stabilized through storage, and finally delivered into AIDC environments, where it is dynamically mapped onto computational processes. As a result, the sustainability attributes expressed by GTI are no longer derived solely from post hoc energy procurement statistics. Instead, they are generated through the coordinated interaction of energy flows, computational flows, and data flows.

The core value of this system lies in transforming green energy from a static supply resource into a dispatchable, coordinated, and measurable infrastructure capability. Within the GTI framework, the proportion of renewable energy usage is not merely the result of procurement decisions. It also reflects the degree of coordination among energy systems, computational systems, and measurement frameworks. Only when renewable energy supply, storage balancing, intelligent grid systems, computational demand, and scheduling mechanisms form a closed-loop system can the sustainability attributes expressed by GTI achieve higher levels of authenticity, continuity, and verifiability.

Integrated “Source - Grid - Load - Storage - Computing”: Synergistic Coexistence



From a forward-looking perspective, the “Source–Grid–Load–Storage–Compute” architecture also leaves room for the evolution of higher-precision GTI measurement. At the current stage, the Full-Scope Aggregate Accounting Method provides a practical and verifiable baseline pathway for GTI implementation. As energy management systems, computational scheduling systems, and power-sector data transparency continue to improve, future development may move toward finer-grained temporal matching, task-level attribution, and cross-regional green compute orchestration, allowing sustainability attributes to evolve from periodic accounting toward more dynamic and precise coordinated generation.

From an industry practice perspective, energy systems for AIDC environments are evolving from single-function power supply capabilities toward system-level coordination capabilities. Renewable energy providers, data center operators, and infrastructure stakeholders may increasingly engage in integrated development across renewable-storage coordination, direct green electricity supply, energy orchestration, and compute adaptation. Such integration enhances the compatibility of renewable energy with high-intensity computational loads, while strengthening the stability of sustainability attributes across both time and space.

This transition suggests that green energy may no longer remain a peripheral component of AI infrastructure. Instead, it may gradually become an integral part of Green AI capability systems. The relationship between energy systems and computational systems may therefore evolve from a traditional “power supply relationship” toward a higher-order “coordinated operational relationship”. The emergence of such capabilities provides a more robust foundation for GTI to move beyond a measurement framework and toward continuous generation and application within real-world computational production environments.

The Future Landscape of Green AI

The development of Green AI remains at an early stage. Its future trajectory will depend on the simultaneous maturation of conceptual frameworks, industrial practice, and collaborative governance mechanisms.
In the near term, related exploration may first take shape through the gradual establishment of GTI terminology systems, evaluation frameworks, and pilot implementation practices, enabling sustainability attributes to formally enter mainstream discussions on AI development.
As standards systems, certification mechanisms, and energy coordination pathways continue to mature, sustainability attributes may progressively evolve from conceptual advocacy into a core evaluation dimension of intelligent infrastructure.
Over time, sustainability may become an increasingly important factor alongside performance and cost within AI infrastructure systems. Meanwhile, a broader ecosystem linking computing power, energy systems, and environmental value coordination may begin to emerge.

From a longer-term perspective, Green AI may ultimately represent more than a technological pathway. It may instead reflect a broader rethinking of the relationship between intelligent growth and energy sustainability.
Under such a paradigm, future AI development may no longer focus solely on maximizing model capability and computational output. Instead, it may place greater emphasis on maintaining a dynamic balance between intelligent expansion and resource constraints.

The introduction of GTI should therefore not be viewed as the endpoint of this evolution, but as an initial starting point. Its long-term value may ultimately lie not only in providing a new language for sustainability measurement, but also in offering a new conceptual foundation for how future intelligent infrastructure can balance innovation with sustainability.

Appendix:
GTI Measurement Methodologies and Accounting Principles
Two Calculation Pathway Formulas

I. Classification of renewable electricity sources:

To unify the measurement scope of green electricity, the electricity consumed by data centers is classified into the following three categories:

On-site renewable generation: solar, wind, and associated storage systems;

Off-site renewable electricity procurement: direct renewable procurement, long-term renewable PPAs, and renewable energy certificates;

Grid-based renewable electricity: the non-fossil share of regional grid electricity.

II. Green electricity weighting and conversion mechanisms:

GTI focuses not only on “whether green energy exists”, but also on whether green energy can form an attributable relationship with actual AI computing activities.

Considering the differences among green electricity from various sources in terms of traceability, temporal matching, spatial matching, dispatch correlation, and actual incremental contribution to green supply, and to avoid the overstatement of green attributes, a weighting factor mechanism needs to be introduced to apply differentiated conversion to different green electricity sources:

On-site renewable generation: Weighting factor = 1

Off-site renewable electricity procurement: Weighting factor = 0.8-1 (determined based on contract and delivery method)

Grid green electricity: Weighting factor = α (0-1)

Note to attribution coefficient α : For electricity sourced from public grids, physical source tracing is generally not possible due to the mixed nature of grid electricity. Hence, GTI incorporates grid-based renewable electricity through a methodology combining “renewable grid share × attribution coefficient”.

Where official statistical data is available, renewable grid shares should be calculated according to publicly disclosed values.

Where data availability remains incomplete, attribution coefficients should be applied to reflect the degree of traceability and temporal matching.

The attribution coefficient α reflects the traceability and temporal matching degree of grid green electricity and can be set differently in different countries and regions based on grid data transparency.

Suggested Attribution Coefficient

Scene	Recommended conversion factors
Only monthly statistical data available	0.8 -1.0
Only quarterly statistical data available	0.6 -0.8
Only annual statistical data available	0.3 -0.6
Unable to verify the source	⩽ 0.3

The calculation should follow a principle of unique attribution in order to avoid double counting across multiple entities, platforms, or accounting systems.

III. Two Measurement Methods:

1. Dynamic Time-Slice Accounting Method:

To reflect the intermittency of wind and solar power generation and the dynamic characteristics of computing power loads, a time-slice method is adopted for refined accounting.

Time-Slice Method (15 min.):

To reflect the fluctuating characteristics of renewable generation and the dynamic nature of computational workloads, a time-slice-based accounting methodology may be adopted. Under this approach, 15-minute intervals may serve as the standardized minimum accounting unit. All green electricity generation, data center IT electricity consumption, computing power task consumption, and AI token output are synchronously measured and accounted based on this time slice. Aggregated statistical accounting at hourly, daily, and monthly levels may be overlaid as needed for refined management purposes.

All on-site renewable systems and externally procured renewable electricity inputs should be equipped with high-precision intelligent metering systems capable of recording:

Actual renewable generation output;

Actual renewable electricity consumption;

Energy storage charging and discharging volumes.

Storage charging electricity should be treated as standard electricity consumption, while the sustainability attributes of discharged electricity should be traced according to the original charging source.

Only when storage charging originates from renewable electricity should discharged electricity contribute to renewable energy attribution.

AI scheduling systems should simultaneously record execution nodes, associated data centers, execution time periods, computational workload volumes, cross-node allocation weights, and final Token outputs in order to establish a multidimensional mapping relationship among tasks, computation, energy consumption, and Token generation.

For each time slice t:

$$\begin{aligned} G(t) &= On-site\ Renewable\ Generation(t) \\ &+ Externally\ procured\ renewable\ electricity(t) \\ &+\ \alpha \times Grid-based\ renewable\ electricity(t) \end{aligned}$$

Independent accounting for energy storage charging and discharging:

Charging is counted as power consumption, while discharging is regarded as green power output, realizing peak shaving and valley filling as well as stabilized green power proportion.

Within each time interval, renewable availability may be calculated as:

Renewable Availability Ratio = G(t) / P(t)

where:

- G(t) represents total electricity demand during time interval t;
- P(t) represents AIDC total electricity demand during time interval t.

Energy management systems (EMS) should support refined and layered metering structures, including:

- Total electricity inflow: Total electricity demand $E_{total}(t)$;
- Segmented IT load $E_{IT}(t)$, cooling, lighting, and backup systems;
- Rack-level PDU: Power consumption per rack $E_{rack}(t)$
- GPU/Server-level (optional, collected via BMC/IPMI): Per-card power consumption $P_{gpu}(t)$.

*AI computational attribution should focus specifically on IT load.

EMS Core Algorithm

Within time slice t:

1. Actual green power consumption of the data center: $G_{used}(t) = \min\left(G(t), E_{IT}(t)\right)$
2. Remaining power supplemented by fossil energy: $E_{fossil}(t) = E_{IT}(t) - G_{used}(t)$
3. Green power ratio of the data center's IT load: $R_{dc}(t) = \dfrac{G_{used}(t)}{E_{IT}(t)}$

This is the baseline green power ratio of the data center at time t.

- The AI platform (e.g., vLLM, TensorRT-LLM, in-house scheduling system) shall output the following for each task / each request:
- List of involved data centers: dc_1、$dc_2 ... dc_n$

Computing power weight contributed by each data center

Total computing power: $W = \Sigma w_i$

Therefore:

Weighted green power ratio of the task: $R_{task} = \Sigma\,[\frac{w_i}{W \times R_{dc_i}(t)}]$

where t refers to the actual execution time window of the task.

A token itself consumes no direct electricity; instead, each unit of token corresponds to a fixed amount of computing power consumption. The model is established as follows:

1. Offline training coefficient:

- FLOPs required for training per 1k tokens
- GPU-seconds required for training per 1k tokens

2. Inference coefficient:

- Different computing power consumption for input tokens and output tokens
- Differentiated coefficients for model sizes (7B/13B/70B/190B)

Final rule:

Green power ratio of a single token = $\boldsymbol{R_{task}}$ of the task that generates the token.

Batch token statistics:

$$GreenPowerConsumption_{tokens} = \Sigma\,(token_i \times PowerPerComputeUnit \times R_{task_i})$$

$$TotalPowerConsumption_{tokens} = \Sigma\,(token_i \times PowerPerComputeUnit)$$

$$OverallGreenPowerRatio_{token} = \frac{GreenPowerConsumption_{tokens}}{TotalPowerConsumption_{tokens}}$$

2. Full-Scope Aggregate Accounting Method

Under the Full-Scope Aggregate Accounting Method, renewable attribution is calculated over an entire accounting cycle.

For single data center:

$$GreenPowerRatio_{DC} = \frac{\int \begin{pmatrix} On-site\ Green\ Power\ Generation + Verified\ Purchased\ Green\ Power + \\ \alpha \times Grid\ Green\ Power)dt \end{pmatrix} dt}{\int (Total\ Power\ consumptionIT)dt}$$

multi-data center, and multi-task environments:

$$GreenPowerRatio_{Token} = \frac{\Sigma(Task\ Computing\ Corresponding\ Energy\ Consumption_i \times DC\ Green\ Power\ Ratio_i)}{\Sigma(Task\ Computing\ Corresponding\ Energy\ Consumption_i)}$$

Where actual energy consumption data is available, it shall be used as the primary basis for allocation. Where energy consumption data cannot be obtained, computing power may be used as an approximate substitute.