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The Digital Footprint of Transparency: A Critical Assessment of the Environmental Impact of Blockchain and AI Infrastructures for Environmental Data Verification

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In recent years, digital notarization technologies, blockchain systems, and artificial intelligence (AI) models have been increasingly proposed and adopted as tools to enhance traceability, immutability, and verifiability of environmental data. In particular, their application in climate and environmental monitoring systems is often justified by the need to improve data reliability, automate verification processes, and reduce risks of manipulation or human error. However, this technological enthusiasm frequently overlooks a fundamental dimension: the direct and indirect environmental impact of the digital infrastructures required to support these systems.

This paper offers a critical assessment of the environmental footprint of blockchain technologies, AI-based verification systems, and digital notarization infrastructures when applied to environmental data governance. The aim is to highlight the paradox of deploying computationally intensive technologies for sustainability purposes that may, in turn, generate significant environmental burdens across their lifecycle.

The analysis is structured along three main dimensions. The first concerns the energy consumption and associated emissions of different computational architectures, including blockchain consensus mechanisms (such as proof-of-work and proof-of-stake) and AI model training and inference processes. Particular attention is given to the role of large-scale data centers, which constitute the shared physical infrastructure underpinning both distributed ledger systems and contemporary AI applications. These facilities represent a

critical yet often under-acknowledged source of electricity demand, cooling requirements, and embodied carbon emissions linked to hardware production and renewal cycles. The second dimension addresses the indirect environmental impact related to the diffusion and scalability of blockchain- and AI-based solutions in environmental data governance. The uncritical adoption of such technologies can lead to the proliferation of overlapping verification systems, redundant computations, and continuously expanding data pipelines. This multiplication of digital infrastructures increases overall system-wide energy demand, often without proportional gains in environmental monitoring efficiency or decision-making effectiveness.

The third dimension explores the risk of technological rebound effects, whereby tools designed to support sustainability objectives inadvertently stimulate increased data generation, processing, storage, and verification activities. AI-driven analytics and automated verification systems, in particular, can contribute to an acceleration of data-intensive practices, further amplifying the environmental footprint of digital ecosystems, even when individual algorithms or systems are optimized for efficiency.

Adopting a systemic and socio-technical perspective, the paper argues that blockchain and AI in environmental contexts should not be evaluated solely in terms of technical performance, automation capacity, or data integrity improvements. Instead, they must be assessed through comprehensive sustainability criteria that incorporate lifecycle environmental costs, infrastructural dependencies, and system-level interactions between computation, energy use, and governance practices.

The contribution engages with broader debates on digital technologies for sustainability and environmental governance, emphasizing that digital infrastructures are not environmentally neutral. Rather, they actively shape the ecological consequences of the systems they support. As such, blockchain and AI should be understood not only as tools for environmental accountability, but also as significant components of contemporary environmental impact.

KEYWORDS:

environmental impact, blockchain, AI, digital infrastructure, energy consumption, sustainability, environmental data verification

RSD TOPIC(S):

Methods, Methodology, & Theory

Introduction: Critical reframing of the hybrid AI–blockchain framework presented at RSD14

In recent years, the issue of sustainability report verification and systemic documentation has acquired an increasingly significant role within environmental governance processes, ESG policies, and the accountability mechanisms of both public and private organizations. This evolution is closely linked to the growing complexity of contemporary production systems, characterized by globalized value chains, high informational fragmentation, and an increasing demand for transparency from institutional, financial, and civic stakeholders [1, 2]. In this context, the ability to verify the reliability of environmental and social data is no longer an ancillary element, but a structural condition for the legitimation of decision-making processes [3]. In parallel, the literature highlights how traditional audit and certification systems exhibit increasing limitations in terms of scalability, timeliness, and their ability to detect complex phenomena such as greenwashing or the selective manipulation of environmental information [4, 5]. These critical issues have fostered the emergence of advanced digital solutions based on distributed technologies and AI systems, capable of partially automating verification and control processes [6, 7].

Within this context lies a previous research stream developed by the authors and presented at RSD14, which explored the potential of blockchain technologies integrated with AI systems for the verification of systemic reports. In particular, the study *Integrating Artificial Intelligence into Blockchain-Based Systemic Report Verification: Towards an AI Protocol for Systemic Analysis* by Liboni, Mucchetti, and Peruccio [8] proposed a hybrid architecture in which blockchain functions as a distributed trust infrastructure, ensuring immutability, traceability, and verifiability of documents, while AI models support the semantic and structural analysis of content [8]. The proposed architecture

is based on a multi-level process integrating Optical Character Recognition (OCR), Natural Language Processing (NLP), and machine learning techniques for the automated identification of inconsistencies, statistical anomalies, and potential indicators of greenwashing. The results of this research showed that the integration of AI and blockchain can significantly enhance the robustness of verification systems, reducing human intervention and increasing the consistency of certification processes [7, 9]. However, the evolution of such systems has also revealed a structural criticality that is often overlooked in the literature: the environmental impact of the computational infrastructures required for their operation. Blockchain systems, AI models, and data centers are indeed technologies characterized by high energy and material intensity, whose large-scale diffusion introduces an internal tension within contemporary paradigms of digital sustainability [10].

This tension can be interpreted as a systemic paradox of the sustainable digital transition: the very tools designed to improve transparency and reliability in environmental governance systems simultaneously contribute to increasing global energy consumption and expanding the ecological and territorial footprint of digital infrastructures [11]. In other words, the digitalization of sustainability is not environmentally neutral, but generates new forms of impact that must be integrated into assessment models [12]. Starting from this contradiction, the present article proposes a critical and systemic evaluation of the environmental impact of blockchain technologies and AI systems applied to environmental data governance. The aim is not to oppose the adoption of such technologies, which have been shown to be effective and valuable in advanced verification processes, but rather to analyze their material and infrastructural implications, contributing to a more comprehensive understanding of the trade-offs between transparency, automation, and sustainability [6, 13].

In particular, the contribution focuses on the so-called “sustainable verification paradox,” understood as the tension between the increasing capacity for control and certification of environmental data and the simultaneous rise in computational resource consumption required to enable such control. To address this issue, the article proposes a structured analysis of the environmental impact of digital technologies across three main dimensions, derived from the literature and the systemic observation of the infrastructures under consideration. Furthermore, an indicative estimate of the

computational footprint associated with the verification of a single report is introduced, with the aim of making explicit the material dimension of processes often regarded as immaterial.

Methodology

This research adopts a qualitative-interpretative systemic approach, consistent with the systemic design paradigm and with systems thinking methodologies applied to the study of complex digital infrastructures. The objective is not the direct empirical measurement of the environmental impact of the technologies under analysis, but rather the construction of a critical and interpretative framework capable of capturing the emerging relationships between computational infrastructures, data verification processes, and sustainability governance dynamics [14].

In this sense, the work is situated within a research tradition that regards digital technologies not as isolated tools, but as constitutive elements of complex socio-technical systems, in which emergent properties cannot be reduced to individual technological components [15]. This perspective is particularly relevant in the case of infrastructures such as the AI-blockchain hybrid, where interactions between computational, algorithmic, and organizational layers produce non-linear effects in terms of energy consumption and environmental impact [16, 17]. This article revisits the AI-blockchain hybrid as a conceptual and operational foundation, while substantially shifting its analytical perspective from informational reliability to infrastructural impact. In other words, technologies previously considered as solutions are here reinterpreted as objects of systemic analysis, in order to highlight the material and computational constraints and conditions that enable their operation. The methodological approach adopted can be described as qualitative, interpretative, and systemic, with a strong component of critical literature analysis. This framework enables the integration of evidence from multiple disciplinary domains, including environmental informatics, digital sustainability studies, computer science, and systemic design [18, 19].

The choice of a non-direct quantitative approach is motivated by the very nature of the phenomenon under investigation. The environmental impacts of AI-blockchain infrastructures do not depend solely on the energy consumption of individual computational operations, but rather emerge from the interaction between digital

architectures, hardware infrastructures, organizational processes, and the dynamics of expansion of information flows [20]. For this reason, a purely technical-engineering analysis would risk reducing the complexity of the phenomenon, overlooking the systemic and relational dimensions that characterize contemporary digital governance. The methodological design is structured into three interdependent levels of analysis, which also constitute the bridge between theory and systemic interpretation.

The first phase consists of a critical review of the scientific and technical literature on the environmental impacts of blockchain technologies, AI systems, and distributed digital infrastructures. This review draws on contributions from multiple disciplinary areas, including computer science, sustainability studies, environmental assessment, and digital infrastructure studies. In particular, the analysis focuses on three main thematic areas: the energy consumption of computational architectures and AI models [21]; the environmental impact of data centers and cloud infrastructures [22]; and rebound effects associated with the digitalization of governance processes and automation [23].

This phase is not merely descriptive; rather, it contributes to the construction of a coherent conceptual field within which to interpret the emerging dynamics of the AI-blockchain hybrid. In this sense, the literature is used not only as a source of empirical findings, but as a tool for identifying systemic relationships, infrastructural contradictions, and feedback dynamics between digitalization and sustainability.

The second phase consists of the decomposition of the AI-blockchain hybrid architecture into its fundamental functional subsystems. This procedure is consistent with a systems thinking approach applied to complex digital infrastructures [24]. The AI-blockchain hybrid is thus broken down into four main layers: data acquisition and digitization (OCR and data ingestion); processing and semantic analysis (NLP and machine learning); anomaly detection and content validation; and certification and notarization on blockchain infrastructure. This decomposition highlights how energy consumption and environmental impact cannot be attributed to a single technological component, but instead emerge from the chain of interactions across different computational layers. In particular, the adopted methodology treats each phase not as an autonomous unit, but as an interdependent node within a broader infrastructural

pipeline characterized by continuous data exchanges, computational demands, and distributed synchronization processes [25].

The third phase concerns the systemic interpretation of the results of the literature review and architectural decomposition. The aim is to construct a coherent set of analytical categories capable of describing the environmental impacts of AI-blockchain infrastructures. From this process, three main categories emerge: direct impacts related to the energy consumption of computational infrastructures; indirect impacts arising from the proliferation and scalability of verification systems; and rebound effects associated with the intensification of datafication processes. These categories are not treated as independent variables, but as interconnected dimensions of the same socio-technical system. They serve as interpretative tools for understanding the central paradox of this work: the increase in verification and transparency capacity simultaneously produces a rise in computational resource demand and in the environmental impact of digital infrastructures.

From a theoretical standpoint, the work lies at the intersection of systemic design, critical digital studies, and environmental informatics. In particular, the research draws on the principles of systems thinking [14], according to which the behavior of complex systems cannot be understood solely through the analysis of their parts, but requires an understanding of the relationships, feedback loops, and emergent dynamics that link technological, organizational, and energetic components. Furthermore, the adopted approach engages with recent perspectives in critical infrastructure theory, which interpret digital infrastructures not as neutral supports of innovation, but as material and political dispositifs capable of shaping the distribution of resources, consumption patterns, and forms of governance [26]. From this perspective, blockchain, AI, and data centers are not merely technological tools, but components of a global infrastructural ecology characterized by high energy intensity and increasing geopolitical centrality. Finally, the methodology integrates a reflexive component typical of systemic design, oriented not only toward the description of phenomena but also toward the understanding of emerging design implications [27]. This allows the AI-blockchain hybrid to be interpreted not merely as a technical innovation, but as a socio-technical configuration that redefines the relationships between sustainability, governance, and computational infrastructures. From a methodological perspective, the contribution of

this paper lies in the construction of an interpretative framework capable of relating energy impacts, digital architectures, and environmental governance processes. Rather than quantitatively measuring a single phenomenon, the research aims to highlight the systemic logics through which the digitalization of sustainability simultaneously generates new capacities for control and new levels of ecological impact.

Analysis of the environmental impacts of AI and blockchain infrastructures

The analysis of the environmental impacts of the AI-blockchain hybrid is situated within the broader reflection on the materiality of digital technologies and their increasing relevance in sustainability governance systems. Although these technologies are frequently represented as “immaterial” tools for optimization, transparency, and automation, recent literature increasingly highlights their fundamentally physical, energetic, and infrastructural nature [12, 20].

From this perspective, the analysis of impacts cannot be reduced to a point-based assessment of the energy consumption of individual operations, but must instead be interpreted as the study of systemic configurations through which blockchain systems, AI models, and data centers interact within global computational ecosystems. These ecosystems are characterized by increasing computational demand, the geographical distribution of infrastructures, and the continuous expansion of data flows [22]. The aim of this section is therefore to reconstruct, from a systemic perspective, the main dimensions through which environmental impacts emerge and become consolidated. These dimensions are not independent, but deeply interconnected, and contribute to defining the central paradox of “digital sustainability verification”: tools designed to enhance environmental transparency simultaneously generate new environmental burdens.

Direct Energy Consumption of Computational Infrastructures

The first dimension concerns the direct energy consumption associated with the execution of computational operations underpinning AI and blockchain systems. This dimension includes the operational energy use of AI models, blockchain consensus mechanisms, and the functioning of data centers that constitute the underlying physical

infrastructure. In the case of blockchain systems, the literature primarily distinguishes between Proof-of-Work (PoW)-based systems and those based on Proof-of-Stake (PoS) or permissioned architectures. PoW systems require substantial and continuous computational power, as block validation is tied to the resolution of complex cryptographic problems. This mechanism entails significantly high energy consumption that scales with network growth [20]. PoS systems substantially reduce per-transaction energy consumption by eliminating computation-intensive competitive mechanisms. However, the literature indicates that reductions in energy intensity do not necessarily translate into lower absolute environmental impacts, due to the increase in transaction volumes and the overall expansion of blockchain networks [28]. In parallel, AI models—particularly those based on deep learning and large language models—exhibit a differentiated energy profile across two main phases: training and inference. The training phase is the most computationally intensive, requiring large datasets, specialized hardware (GPU/TPU), and extended processing times [29]. The inference phase, although less demanding per individual operation, becomes significant when scaled to millions or billions of requests. A central element of this dimension is the role of data centers, which constitute the shared physical infrastructure underlying both AI systems and blockchain networks. Data centers represent one of the most critical nodes of the contemporary digital economy, characterized by high electricity consumption, the need for advanced cooling systems, and environmental impacts associated with the production and replacement of hardware [22]. In particular, the notion of embodied carbon is increasingly relevant, referring to the environmental impact associated with the full life cycle of hardware infrastructure. From a systemic perspective, these elements cannot be considered in isolation, but rather as interdependent components of a global computational infrastructure. The increasing demand for verification, transparency, and automation directly contributes to the expansion of required computational capacity, generating a feedback loop between sustainability-driven demand and digital resource consumption [16].

Indirect Impacts and Systemic Proliferation of Infrastructures

The second dimension concerns the indirect impacts associated with the diffusion and scalability of AI and blockchain technologies within environmental governance systems. Unlike direct impacts, this dimension emerges at a systemic level and relates to the

overall structure of digital infrastructures. One of the most relevant aspects highlighted in the literature is the tendency toward the proliferation of parallel verification systems. In the absence of shared standards and interoperable infrastructures, the adoption of AI and blockchain solutions in environmental certification processes tends to generate a multiplication of platforms, protocols, and databases [30]. This phenomenon produces a duplication of computational activities and validation processes, resulting in an increase in overall energy consumption. In other words, the fragmentation of digital infrastructure generates systemic inefficiencies that translate into a greater environmental impact compared to an integrated system [1].

A further critical element concerns the increasing integration of AI and blockchain within hybrid architectures. Although such systems are designed to enhance verification quality and reduce the risk of data manipulation, they introduce additional layers of computational complexity. Each stage of the pipeline—from data collection to semantic processing, and ultimately to blockchain registration—contributes to increasing the overall system load. This cumulative effect is particularly relevant in environmental governance systems, where the volume of generated data is continuously growing. From a systemic perspective, this dynamic can be interpreted as a process of “infrastructural accumulation,” in which each new demand for transparency generates additional layers of digital processing and recording. This process is not linear, but characterized by reinforcing feedback loops that progressively amplify resource consumption [14].

Rebound Effects and Intensification of Datafication

The third dimension concerns so-called rebound effects, which have been widely discussed in the literature on energy efficiency and digital technologies. The underlying principle is that improvements in technological efficiency do not necessarily lead to a reduction in overall environmental impact; instead, they may incentivize increased resource use. Within the context of AI and blockchain systems applied to environmental governance, this phenomenon primarily manifests through the intensification of datafication processes. The introduction of automated analytical tools and continuous monitoring systems leads, in fact, to an increasing production, collection, and storage of environmental data. AI systems, particularly those used for anomaly detection and semantic verification of reports, contribute to the transformation of governance

processes into “always-on” systems. This results in a significant increase in the volume of data being processed and stored. Even in the presence of improvements in algorithmic efficiency, the overall effect may still be an increase in total energy consumption, driven by the exponential growth in demand for analysis and verification [28]. From a systemic perspective, this phenomenon highlights a decoupling between local efficiency and global impact. Micro-level optimizations can generate macro-level effects that run counter to intended outcomes, further reinforcing the paradoxical nature of sustainability digitalization.

Case study and quantification of the computational footprint of AI–blockchain verification

This section introduces a case study aimed at estimating the computational footprint associated with the adoption of a hybrid AI–blockchain architecture for sustainability report verification. This analysis is situated within the emerging literature on the sustainability of digital infrastructures and the materiality of datafication processes, which highlights how even “immaterial” computational operations produce measurable and cumulative energy impacts. The case study is based on the architecture proposed in a previous study by the authors, in which an integrated AI–blockchain system is used for the automated validation of systemic reports through a pipeline composed of OCR, NLP and machine learning models, anomaly detection, and blockchain-based notarization [8]. The aim of the present contribution is not to restate the model itself, but to reinterpret it in terms of energy consumption and infrastructural impact. From this perspective, the system is conceptualized as a complex computational unit whose impact does not depend on a single operation, but rather on the concatenation of multiple interdependent computational stages.

Modeling of the AI–blockchain verification process

The verification process can be decomposed into four main stages: document acquisition and digitization (OCR), semantic analysis via NLP/LLM models, anomaly detection and consistency checking, and final recording on a blockchain through smart contracts. This structure reflects the typical architecture of document intelligence and digital verification systems, in which multi-layer computational pipelines integrate AI techniques and distributed infrastructures [21, 29]. Each stage presents a distinct

energy profile, influenced by the type of model employed, the complexity of the document, and the underlying hardware infrastructure. The literature in fact highlights that energy consumption in AI systems is not linear, but depends on factors such as input length, model size, and the number of required inference operations [28].

Detailed estimation of energy consumption per verification stage

In order to make explicit the material dimension of the AI-blockchain verification system, this section provides a disaggregated estimate of energy consumption for each stage of the pipeline. The adopted approach is consistent with the literature on digital infrastructure studies, which emphasizes the need to decompose complex computational systems in order to understand their emergent impacts. The total consumption per report is therefore expressed as the sum of the verification steps.

The first stage concerns the conversion of the document into a machine-readable digital format. Optical Character Recognition (OCR) techniques represent a preliminary and essential step in document AI pipelines. The literature indicates that OCR energy consumption typically ranges between 0.1 and 0.5 Wh per document, depending on image quality and text length [31]. In the present model, an average operational value of $\text{OCR} \approx 0.3$ Wh per report is assumed.

The second stage represents the most computationally intensive core of the system. It includes the use of NLP models and, in some cases, large language models for semantic content analysis, logical and textual consistency checking, identification of potential greenwashing indicators, and classification with respect to ESG frameworks. Recent studies show that inference energy consumption ranges from 0.2 to 2 Wh depending on the model used [21].

Within the proposed pipeline, multiple inference steps are considered: primary NLP inference: 0.4–1.2 Wh; secondary semantic analysis: 0.2–0.6 Wh; additional consistency checks: 0.1–0.3 Wh. The overall energy consumption of the AI component is therefore: $\text{AI/NLP} \approx 0.7\text{--}2.1$ Wh (average ≈ 1.4 Wh).

The third stage concerns anomaly detection models and structural data validation. This component is generally less intensive than NLP models, as it is based on statistical methods or lighter machine learning approaches. The literature on data verification systems reports typical energy consumption values between 0.05 and 0.4 Wh per

document. In the present study, a value of Anomaly detection ≈ 0.2 Wh per report is assumed.

Blockchain notarization

The final stage consists of recording the verification outcome on the blockchain via smart contracts. Energy consumption varies significantly depending on the type of infrastructure used. In the case of permissioned systems or Proof-of-Stake architectures, the literature reports substantially lower energy consumption compared to Proof-of-Work systems, typically below 0.5 Wh per transaction [20, 22]. In the proposed model, Blockchain ≈ 0.3 Wh per report is assumed. Aggregating the components of the previous stages yields an estimated total of ≈ 2.2 Wh per report, equivalent to 0.0022 kWh. This value can be converted into CO₂e emissions, resulting in approximately 0.66 gCO₂e per report. Although this unit value may appear limited, its relevance becomes evident from a systemic and scalable perspective. In environmental governance systems, verification does not occur on isolated documents but on continuous flows of ESG reports and corporate audits. In this scenario, energy consumption increases linearly with the volume of documents, while being embedded within a potentially exponential growth context of verification demand, even if remaining relatively contained at the unit level [12].

Discussion and conclusions

The analysis presented in the previous sections highlights how the integration of blockchain and AI within environmental reporting verification systems introduces a profound transformation not only at the technical level, but more importantly at the systemic and environmental level. The technologies under consideration do not operate as neutral tools supporting sustainability governance; rather, they function as active infrastructures that reshape the material and operational conditions of environmental data production, management, and validation [26, 32]. From this perspective, a structural tension emerges between two simultaneous and seemingly convergent yet substantively contradictory trajectories. On the one hand, the evolution of AI and blockchain technologies enables a significant increase in transparency, verifiability, and automation in environmental auditing and reporting processes [7]. On the other hand,

this evolution entails an increase in the computational, energy, and infrastructural resources required to sustain these very processes [29].

This tension can be interpreted as a systemic paradox of sustainability digitalization, whereby improvements in monitoring and control capacity simultaneously generate an increase in the environmental impact of the system that enables them. This dynamic resonates with the literature on the ecological limits of digital transformation and with the need to conceptualize computational technologies as material systems embedded within global energy and infrastructural chains [33, 34]. A first point of discussion concerns the redefinition of the analytical boundary of sustainability. Traditionally, environmental assessments focus on the final objects of governance—products, organizations, supply chains, or industrial processes—while overlooking the digital infrastructures that make sustainability measurement itself possible [35]. The analysis proposed in this study instead shows how data centers, AI models, and blockchain networks must be considered integral components of environmental governance systems, rather than mere supporting tools.

This systemic boundary redefinition is particularly relevant in the context of contemporary ESG practices, which are increasingly dependent on cloud platforms, automated monitoring systems, and continuous data processing workflows. In this sense, digital sustainability cannot be interpreted solely as the ability to collect more accurate information, but requires a comprehensive assessment of the environmental impact of the infrastructures that produce, store, and process such information [19].

Secondly, a key issue emerges concerning systemic feedback dynamics. The introduction of AI-blockchain systems in verification processes does not merely improve information quality, but also reshapes decision-making and organizational structures themselves. The availability of automated analytical tools and distributed notarization mechanisms fosters an increase in data production, greater information granularity, and a continuous expansion of information flows [36]. This generates a reinforcing feedback loop between analytical capacity and data production, contributing to the expansion of the system itself. In systems thinking terms, this dynamic can be interpreted as a process of self-amplifying informational complexity, in which increases in computational capacity do not reduce system complexity but instead intensify it [17].

The intensification of datafication processes also takes on cultural and organizational dimensions. The growing availability of automated analytical tools tends to position data as a central element of contemporary governance, encouraging continuous data collection, permanent storage practices, and real-time monitoring. This transformation produces a gradual normalization of the digital infrastructuring of sustainability, making the environmental impacts of the underlying technologies increasingly invisible [37].

A third element concerns the issue of design proportionality in digital infrastructures. The adoption of increasingly sophisticated verification systems risks producing computational architectures that are oversized relative to their actual informational value. In other words, there is no linear relationship between computational intensity and the quality of environmental governance. This observation opens a fundamental reflection for systemic design: the need to introduce design criteria based not only on efficiency, but also on “computational sufficiency,” understood as the capacity to balance informational value and environmental cost of digital infrastructures [38].

From this perspective, the concept of computational sufficiency represents a potential theoretical advancement over traditional technological optimization logics. While efficiency aims to reduce energy consumption per operation, sufficiency introduces a systemic reflection on the necessity of computational operations themselves, their scale, and their proportionality with respect to intended objectives [39]. This distinction is particularly important in the case of AI-blockchain infrastructures, where the continuous expansion of computational capabilities risks producing systems characterized by increasing energy and material complexity. The literature on digital infrastructures indeed shows that improvements in technological efficiency do not automatically lead to reductions in absolute consumption, especially in the presence of scalability effects and growing computational demand [23].

Another relevant issue concerns the relationship between automation and responsibility in environmental governance processes. The introduction of automated verification systems progressively shifts trust from institutions and human actors toward algorithmic and distributed infrastructures. While this transformation may enhance the technical reliability of certification processes, it also introduces new forms of infrastructural dependence and new asymmetries of control related to access to computational technologies [40]. Algorithmic governance of sustainability may also

produce increasing systemic opacity. Paradoxically, systems designed to enhance environmental transparency can themselves become difficult to interpret due to the complexity of their underlying technological architectures. This issue is particularly evident in deep learning-based AI models, which are characterized by high predictive performance but limited explainability [41].

Finally, the case study analysis shows that even systems designed to optimize transparency and reduce the risk of greenwashing may indirectly contribute to the generation of new environmental impacts. This does not imply a judgment of technological ineffectiveness regarding AI and blockchain, but rather highlights the need to redefine the criteria through which these technologies are integrated into sustainability governance systems [18]. From this perspective, systemic design plays a central role in rethinking contemporary digital infrastructures. Rather than developing increasingly computationally intensive systems, the challenge lies in designing proportionate, interoperable, and environmentally sustainable architectures capable of balancing informational transparency, energy efficiency, and infrastructural resilience.

Limitations and future directions

This study presents several limitations which also constitute opportunities for future research developments.

First, the analysis is based on a theoretical-systemic reconstruction supported by the literature and aggregated estimates, without large-scale empirical validation through direct measurements in real operational environments. This limits the absolute precision of the energy estimates, while preserving their interpretative validity at a systemic level. Second, the rapid evolution of AI and blockchain technologies introduces significant variability in the energy parameters of the systems under analysis. Model efficiency, hardware optimization, and innovations in distributed architectures may alter estimated values over time, making continuous updates of analytical frameworks necessary. Third, the study does not include a systematic comparison with non-digital or semi-digital alternatives to reporting verification processes. Such a comparison could contribute to a more comprehensive assessment of the trade-offs between informational efficiency and environmental impact. Future research directions may include the integration of Life Cycle Assessment (LCA) models specifically adapted to AI–

blockchain infrastructures, the development of “computational sustainability” metrics, and comparative analyses across different verification architectures (centralized, distributed, and hybrid). Finally, a particularly relevant research avenue concerns the development of systemic design models aimed at reducing computational overconsumption, through the introduction of multi-objective optimization criteria that simultaneously include informational accuracy, transparency, and environmental impact.

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