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Optimizing Green Business Information Management Systems Through Carbon-Neutral Digital Transformation Pathway Design

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Abstract

This research develops a comprehensive framework for optimizing green business information management systems to achieve carbon neutrality goals through digital transformation. The study conducted cross-sector carbon footprint assessments of information systems across six industries, analyzing emission patterns based on operational scales, industry characteristics, and technological architectures. A multi-tiered optimization model was developed targeting infrastructure, data management, and application layers, validated through empirical data from enterprises undergoing digital transformation. Results reveal a strong negative correlation ($r = -0.73$) between digital maturity indices and emission intensity, with organizations implementing comprehensive digital transformation achieving average carbon reductions of 31% over five years. The proposed multi-tiered optimization approach enabled 42.6% emission reductions, with technology companies achieving 68% reductions. Economic analysis demonstrates return on investment ranging from 132-278% over five-year periods, with payback periods of 14-36 months. This study advances information management theory by integrating technological architecture with environmental performance governance, providing quantifiable carbon assessment methodologies across system layers and practical implementation matrices for industry-specific applications. The framework enables organizations to balance carbon reduction objectives with operational efficiency, addressing the critical gap between theoretical potential and practical implementation in carbon-neutral transformations.

Keywords: Green Information Management Systems; Carbon Neutrality; Digital Transformation; Sustainability Optimization.

1. Introduction

The global pursuit of carbon neutrality has emerged as a crucial response to the deteriorating environmental issues that affect almost all business sectors [1]. Information management technologies have been viewed as systems that not only streamline business activities but also significantly influence the carbon footprint of the business in terms of energy consumption and resource utilization [2]. Recently, there has been increased attention directed towards the environmental impacts of information systems, prompting scholars to develop more digitally friendly approaches to transformations aimed at supporting systemic carbon neutrality objectives for environmental goals [3]. The integration of green practices within information management alongside digital transformation presents significant opportunities for enhancing operational efficiency and performance for businesses in a carbon-constrained environment [4].

Recent advances in digital transformation for carbon neutrality reveal both progress and gaps. Han et al. [5] demonstrated digital platforms' role in carbon neutral innovation varies by region. Zhang et al. [6] confirmed circular

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economy and digitalization drive decarbonization in G7 countries. Han et al. [7] identified external pressure as a key moderator in digital transformation's carbon impact. Pourhejazy et al. [8] noted current supply chain initiatives lack comprehensive approaches. However, these studies focus on macro-level impacts without providing systematic optimization frameworks for business information systems. Actionable methodologies for multi-layered carbon reduction while maintaining operational efficiency remain absent. This research gap is particularly critical as organizations face increasing pressure to achieve carbon neutrality while maintaining competitiveness.

These goals have induced remarkable operational and technological changes across various fields, which require a complete change in management and information systems [9]. The shift to net-zero carbon emissions requires complex carbon accounting, monitoring, and optimization along with minimal self-inflicted environmental damage from the information systems [10]. Information systems are required by organizations to facilitate automated resource scheduling, energy savings, and emissions tracking in sophisticated organizational systems [11]. Supporting these systems is vital due to the 2-3% contribution the IT industry makes to global carbon emissions, as showcased by Raja's study that IT companies need to adopt greener computing within their digital infrastructures [12].

Digital transformation initiatives establish primary competencies which enable achieving carbon neutrality targets through improved data infrastructure, data collection, analytics, and decision support systems [13]. With the implementation of green information systems, companies have recorded considerably enhanced environmental performance, including average emissions reductions ranging from 15% to 25% in diverse operational contexts [14]. The evolution of green information technologies has created unprecedented opportunities for the integration of sustainability into core business functions by employing sophisticated monitoring, predictive analytics, and automated optimization [15]. While these systems show operational benefits, critical gaps remain. Literature lacks quantitative methodologies for carbon footprint assessment across system layers and optimization frameworks balancing environmental with operational objectives. Organizations need practical implementation guidance to maximize carbon reduction. This disconnect between theoretical potential and practical application limits transformation effectiveness. The synergy of geographic information systems and lifecycle assessment techniques allows exhaustive carbon footprint analysis across value chains, supporting the creation of economically and environmentally beneficial performance strategies [16].

Carbon-neutral policies are increasingly acknowledging, as discussed in Wei et al. [17], that information systems serve as critical facilitators for transforming businesses into low- and carbon-emitting entities. An information architecture capable of sophisticated sustainability data processing requires advanced silos for strategic and operational decision-making at organizational ecosystems at carbon neutrality [18]. Research conducted on managing low carbon emissions in supply chains emphasizes the remarkable advantages of integrated information systems in several physically dispersed organizations networks mapped or scoped to implement and coordinate sustainability activities [19]. Such systems assist in the real-time monitoring of emissions, refinement of compliance management to expedite compliance processes, and the management of business operations towards carbon emission reduction targets.

This study develops an integrated optimization framework addressing these gaps through quantitative assessment methods and progressive implementation pathways across infrastructure, data management, and application layers. Our multi-tiered approach enables organizations to achieve measurable carbon reductions while enhancing operational performance. Section 2 presents methodology including system framework, carbon assessment, and optimization models. Section 3 reports cross-sector empirical results. Section 4 discusses implications. Section 5 concludes.

2. Design and Methodology

2.1. Green Business Information Management System Framework Design

This work proposes a novel approach to the green business information systems management by incorporating an element of environmental sustainability alongside advanced information technology frameworks. Following the foundational work of Sarkis et al. [10], the framework includes four layers nested within an overarching governance model that aligns with organizational sustainability goals and compliance obligations. Figure 1 depicts the data acquisition layer that harvests internal data from enterprise subsystems associated with monitoring energy, materials, and processes, as well as external data from regulatory databases and environmental monitoring systems. The processing infrastructure layer leverages cloud computing to implement big data technologies, analytics engines, machine learning models, and visualization methods that present carbon-related information in decision-useful formats, as emphasized by Guan et al. [20]. This cloud-based approach reduces the system's overall carbon footprint by optimizing resource utilization and eliminating redundant on-premises infrastructure. The modules layer encompasses carbon accounting and emission tracking across Scopes 1-3, while the user interface layer provides stakeholder-specific dashboards for decision-making at all organizational levels. These resources operate dynamically to support effective carbon management across diverse operational scenarios. As Dalene [21] notes, such adaptive information management capabilities are crucial for maintaining optimal environmental performance in complex organizational environments.

This multi-level system sits within a governance structure that polices carbon management across the company, allowing corporations to control, study, and enhance their operational carbon flows while still being agile and competitive during the shift to carbon neutrality. To demonstrate the practical application of this framework, we examine its implementation in a real-world financial services context. The bank's branch network of 2,500 locations feeds energy data into the system through IoT sensors. Energy consumption patterns emerge from readings taken at 15-minute intervals throughout each business day. The cloud-based system processes 50TB of operational data each month. This analysis revealed that morning startup routines drive energy use 40% above baseline levels. When the carbon accounting system calculated total annual emissions at 15,200 tCO_2e, data centers emerged as the primary contributor at 68%. The assessment also identified opportunities to reduce emissions by 35% through strategic interventions. Different user groups access customized dashboards suited to their responsibilities. Facility managers track real-time consumption while executives monitor strategic carbon reduction progress. Within 18 months, the bank reduced emissions by 22% and achieved significant operational cost savings.

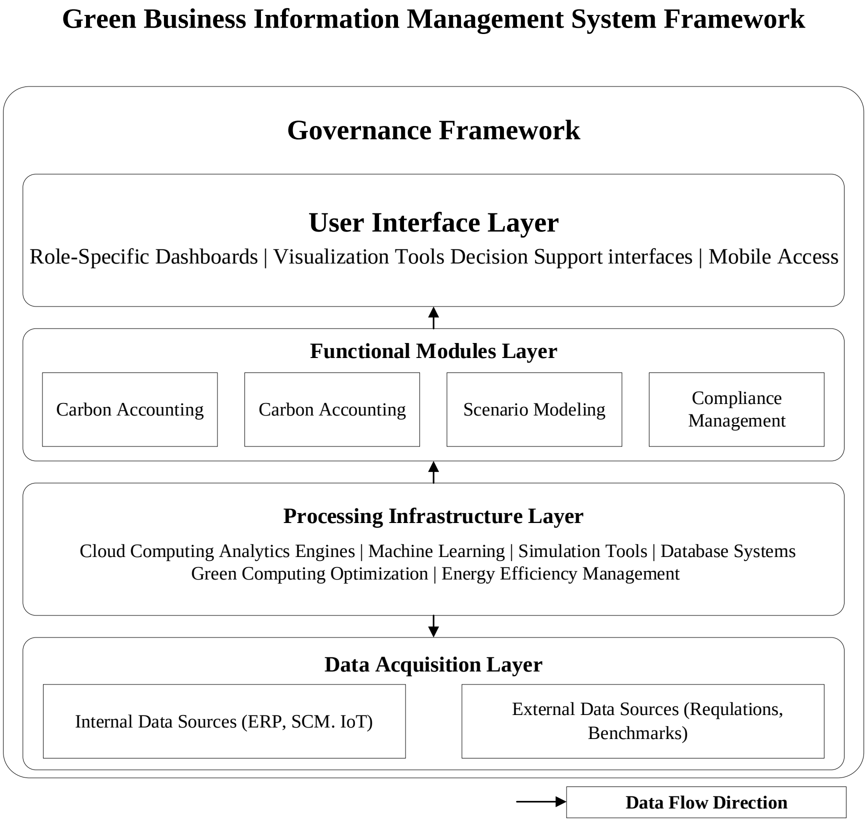

Figure 1. Green business information management system framework

2.2. Information System Carbon Footprint Assessment Method

Considering the carbon footprint of an information system is critically important for developing a strategy towards carbon neutrality. Following Raja's [12] and Dias & Arroja's [22] work, this paper proposes a comprehensive approach for assessing the carbon emissions associated with business information management systems throughout their lifecycle.

The information systems' carbon footprints incorporate operating energy emissions as well as hardware, software, and end-of-life system disposal emission impacts throughout the system's lifecycle. The energy consumed in the system's operational phase mainly incurs direct emissions, while indirect emissions encompass carbon contained within the hardware components, emissions associated with software development, and debris disposal associated with the system at the end of its useful life. The outlined carbon footprint total for an information system can be expressed as:

$$CF_{tot} = CF_{dir} + CF_{ind} \tag{1}$$

where, CF_{dir} represents direct operational emissions and CF_{ind} represents indirect emissions throughout the system lifecycle. Direct emissions calculations are primarily done with the following formula:

$$CF_{dir} = \sum_{i=1}^{n} (E_i \times EF_i) \tag{2}$$

where, E_i represents the energy consumption of component i in kilowatt-hours (kWh), EF_i represents the emission factor for the relevant energy source in $kgCO_2e/kWh$, and n represents the number of system components. Carbon footprint calculation methodologies follow established frameworks reviewed by Li et al. [23], with lifecycle inventory data sourced from the Ecoinvent database [24]. For server systems operating in a cloud environment, Uddin et al. [25] propose a revised formula that takes into account the server utilization rates:

$$CF_{cld} = \sum_{j=1}^{m} (P_j \times U_j \times T_j \times EF_j) \quad (3)$$

where, P_j represents the power consumption of server j at full utilization in kilowatts (kW), U_j represents the utilization rate of server j as a percentage, T_j represents the operational time in hours, and EF_j represents the emission factor for the energy source powering server j ($kgCO_2e/kWh$), and m denotes the total number of servers. To illustrate the application, consider a data center with 20 servers, each consuming 0.5 kW at 65% utilization rate. Operating continuously (8,760 hours annually) with a typical grid emission factor of 0.438 $kgCO_2e/kWh$, the calculation yields: CF_{cld}= 20 × 0.5 × 0.65 × 8,760 × 0.438 = 24,940 $kgCO_2e$ annually. Cloud migration scenarios typically improve utilization to 85% while reducing server count by 60%, potentially achieving 40% emission reduction.

Indirect emissions are calculated using a lifecycle assessment approach:

$$CF_{ind} = CF_{mfg} + CF_{trp} + CF_{dev} + CF_{dsp} \quad (4)$$

where, CF_{mfg} represents emissions from manufacturing, CF_{trp} from transportation, CF_{dev} from development processes, and CF_{dsp} from disposal activities.

The carbon intensity related to information processing (CI_{inf}) is an important benchmark to measure numerous systems used in managing information:

$$CI_{inf} = \frac{CF_{tot}}{D_{prc}} \quad (5)$$

where, CF_{tot} represents the total carbon footprint calculated from Equation 1 measured in tCO_2e, and D_{prc} represents the volume of data processed during the assessment period in TB. The measure will allow companies to measure their carbon efficiency in their information systems and identify areas that need improvement.

In order to account for temporal variations related to carbon impacts, we calculate the following time-weighted carbon footprint (CF_{wgt}):

$$CF_{wgt} = \sum_{t=1}^{T} (CF_t \times \delta_t) \quad (6)$$

where, CF_t represents the carbon footprint at time period t, δ_t represents the temporal weighting factor, and T represents the total number of time periods in the assessment.

For comparative analysis between systems, a relative carbon efficiency index (*CEI*) is introduced:

$$CEI = \frac{CI_{inf,bl}}{CI_{inf,cr}} \times 100 \quad (7)$$

where, $CI_{inf,bl}$ represents the carbon intensity of the baseline system and $CI_{inf,cr}$ represents the carbon intensity of the current system. A CEI above 100 suggests that there has been a positive change in carbon efficiency relative to the baseline.

To aid in the implementation of carbon reduction strategies and guide governance decisions along with the scope of a digital transformation program, a *MCRV* is set which stands for Marginal Carbon Reduction Value:

$$MCRV = \frac{\Delta CF_{tot}}{\Delta Inv} \quad (8)$$

where, ΔCF_{tot} represents the change in total carbon footprint and ΔInv represents the incremental investment required for implementation. It permits businesses to prioritize actions aimed at reducing carbon emissions relative to investment made.

This analytical structure aids firms in distinguishing significant carbon contributors within their information systems, establishing standard emission levels, and estimating the potential advantages of reducing carbon emissions for various options of digital transformation. This framework develops information management strategies that integrate emissions management within the context of organizational carbon neutrality goals by offering an integrated assessment of direct and indirect emissions, thus fostering intelligent decision-making during the digital transformation.

2.3. Digital Transformation Pathway Optimization Model

Incorporating sustainability into business management models alongside other strategies requires purposeful strategizing to achieve carbon reduction while maintaining operational streamlining and financial health. Based on the studies by Yang et al. [26] and Zampou et al. [27], we propose an integrated multi-objective optimization model that enables firms to choose the most appropriate pathways for the transformations needed for organizations to achieve their carbon neutrality goals.

These components of digital transformation optimization are defined by three core aspects: an organizational carbon footprint (*C*), an organizational level performance (*P*), and an implementation capability (*F*). The grand optimization function integrates carbon impact, business performance, and feasibility into one evaluation metric, enabling holistic pathway assessment rather than isolated optimization. The grand optimization function (*Z*) can be formulated as:

$$Z = \max\left(\alpha \times \frac{C - C_{min}}{C_{max} - C_{min}} + \beta \times \frac{P - P_{min}}{P_{max} - P_{min}} + \gamma \times \frac{F - F_{min}}{F_{max} - F_{min}}\right) \tag{9}$$

where, α, β, and γ refers to weights allocated to the carbon impact, business performance, and implementation feasibility, respectively, in addition to $\alpha + \beta + \gamma = 1$. The variables C_{min}, P_{min}, F_{min}, and C_{max}, P_{max}, F_{max} represent the minimum and maximum possible values for each dimension, enabling normalization across different measurement scales. Weight determination employs multi-criteria decision methods combining expert judgment through structured approaches with organizational benchmarks [28]. The method integrates qualitative assessments from stakeholders with quantitative performance metrics, allowing flexible calibration based on sectoral priorities and organizational contexts.

The carbon impact dimension (*C*) is quantified using a composite index that incorporates both absolute carbon reduction potential and relative improvement efficiency:

$$C = \omega_1 \times \Delta CF_a + \omega_2 \times \frac{\Delta CF_r}{I} \tag{10}$$

where, ΔCF_a represents the absolute carbon footprint reduction (in tCO_2 e), ΔCF_r represents the relative improvement percentage, *I* represents the required investment, and ω_1 and ω_2 are weighting factors with $\omega_1 + \omega_2 = 1$.

The business performance dimension (*P*) is evaluated using a weighted combination of key performance indicators:

$$P = \sum_{i=1}^{n} w_i \times K_i \tag{11}$$

where, K_i represents the normalized value of the *i*-th key performance indicator, w_i represents the corresponding weight, and $\sum_{i=1}^{n} w_i = 1$.

Following Yao et al. [29], the implementation feasibility dimension (*F*) incorporates technical readiness, organizational capability, and transition risk factors:

$$F = \delta_1 \times T_r + \delta_2 \times O_c - \delta_3 \times R_t \tag{12}$$

where, T_r represents the technical readiness level, O_c represents organizational capability, R_t represents the transition risk factor, and δ_1, δ_2, and δ_3 are weighting coefficients with $\delta_1 + \delta_2 + \delta_3 = 1$. Simultaneous three-layer implementation faces barriers including resource constraints, system integration complexity, and organizational coordination challenges, necessitating the staged approach in Equation 14.

The optimization model is subject to several constraints, including budgetary limitations, time constraints, and minimum performance requirements:

$$\begin{aligned} &\sum_{j=1}^{m} x_j \times C_j \le B_t \\ &\max_{j \in 1,2,\ldots,m} (x_j \times T_j) \le T_m \\ &P \ge P_t \end{aligned} \tag{13}$$

where, x_j is a binary decision variable indicating whether transformation option j is selected (1) or not (0), C_j and T_j represent the cost and implementation time for option j, B_t represents the available budget, T_m represents the maximum allowable implementation timeframe, and P_t represents the minimum acceptable business performance level.

Consider a hypothetical 5,000 tCO_2e enterprise comparing cloud migration versus infrastructure optimization. With weights α=β=0.4, γ=0.2, the model balances investment costs against emission reduction potential, demonstrating multi-objective optimization dynamics.

The model employs a staged implementation approach, defining the transformation pathway as a sequence of implementation phases:

$$Path = S_1, S_2, ..., S_k \tag{14}$$

where, *Path* represents the complete transformation pathway, $S_1, S_2, ..., S_k$ denote the sequential implementation stages from first to last, and k indicates the total number of stages.

Each stage represents a distinct set of transformation initiatives to be implemented concurrently. The interdependencies between different initiatives are captured through precedence constraints:

$$\sum_{t=1}^{T} t \times y_{i,t} \leq \sum_{t=1}^{T} t \times y_{j,t} \tag{15}$$

where, $y_{i,t}$ is a binary variable indicating whether initiative i is implemented at time period t, and initiative j depends on the prior implementation of initiative i.

To address the dynamic nature of digital transformation, the model incorporates an adaptive learning component that updates pathway parameters based on implementation feedback:

$$\theta_{t+1} = \theta_t + \eta \times \nabla Z(\theta_t) \tag{16}$$

where, θ_t represents the model parameters at time t, η represents the learning rate, and $\nabla Z(\theta_t)$ represents the gradient of the objective function with respect to the parameters. The adaptive mechanism updates parameters iteratively based on implementation outcomes, with conservative learning rates preventing system instability while enabling gradual optimization.

The optimization problem employs integer programming for project selection integrated with dynamic programming for execution sequencing. This unified approach enables organizations to implement phased transformation that maximizes carbon reduction while maintaining operational continuity, determining optimal execution sequences for achieving carbon neutrality.

2.4. Data Collection and Analysis Process

An all-encompassing green business information management system review requires a blended approach of carbon footprint accounting and operational performance metrics that is methodically grounded. This study integrates the frameworks proposed by Bhatia et al. [30] and He et al. [31] sequentially to devise an orderly multi-phase process for systematic evaluation of the environment's impact from information systems and the most effective pathways for digital transformation. The process begins with set data collection that commences with listing system components ranging from hardware infrastructure to software packages, network equipment, and data centers. The data collection encompasses functional specifications and operational details for baseline configuration profile development. Following Mao et al.'s [32] work, this study employs a combined measurement approach involving direct instrumentation, simulation modelling, and analytical estimating to address the sophisticated high dimensionality of carbon impacts associated with information systems. Energy-use operational metering data for smart meters and power distribution units provide trend data for the server system's energy consumption. System use trends are also monitored through employing performance monitoring tools that report process load, memory and network consumption. These primary data collection frameworks were supplemented with secondary data consisting of lifecycle emission factors, embodied carbon metrics, and requisite industry benchmarks for an all-inclusive analysis.

Constructed Carbon Footprint Framework was figured out in section 2.2 and involves carbon footprint calculation algorithms that take into account the pre-processed data aimed at quality and consistency as presented in Figure 2. The analysis of carbon focuses on ensuring synergies with performance measurement and estimating operational efficiency recursively across several business processes for the purpose of generating optimized recommended solutions tailored to prioritized needs in view of achieving carbon neutrality goals within the entity. The entire process features closure that enables continuous enhancement operationalized through collection of routine data incrementally refining techniques aligned with emerging best practices which enables new best practices to be added to existing ones in a smooth and uncomplicated manner through refinement of concepts and techniques targeted analytical frameworks and concepts design steps make strategies formulated adaptable to changing technologies and innovative business needs. Such a rounded approach guarantees initiatives towards digital transformation are not only aimed at achieving carbon neutrality goals but also anticipate future technological changes and emerging needs of the business enabling shift responsive frameworks.

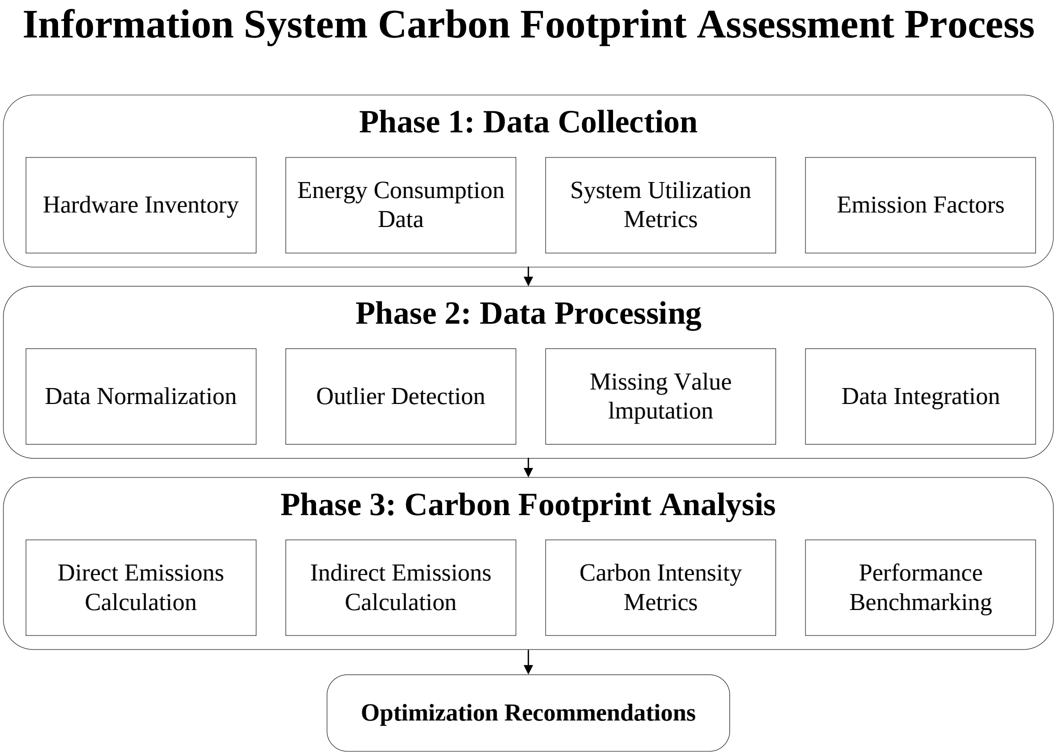

Figure 2. Information system carbon footprint assessment process

3. Results

3.1. Carbon Emission Status Analysis of Business Information Management Systems

Business Information management systems constitute a vital piece of the puzzle when it comes to assessing a firm's environmental footprint, albeit an often overlooked one. A thorough assessment within frameworks of varying business geographies reveals sophisticated emission patterns that are highly dependent on the industry makeup, scale of production, and technologies in use. As Table 1 shows, financial services have the highest overall emissions (7,850 to 12,400 tCO_2e per year) that mainly result from their large data centers, while tech companies have comparatively less emission intensity (74 to 125 $kgCO_2e$/TB) despite their high computational demands. Manufacturing enterprises generate moderate emission levels (4,200-8,600 tCO_2e) with operational technology systems constituting their primary emission source (52%). Technology companies achieve 68% reduction potential through cloud-native architectures eliminating legacy infrastructure dependencies, contrasting sharply with manufacturing's operational constraints and financial services' compliance-driven system rigidity.

The research identifies a strong negative correlation ($r = -0.73$) between digital maturity indices and emission intensities, with organizations implementing comprehensive digital transformation initiatives achieving average 31% carbon footprint reductions over five-year periods. As illustrated in Figure 3, servers and computational infrastructure represent the dominant emission source in both on-premises (42%) and cloud-based deployments (38%), followed by storage systems (21% and 25% respectively), enabling targeted mitigation strategies. Deployment architecture significantly influences emissions, with cloud-based implementations demonstrating 27% lower carbon footprints through improved resource utilization and cooling efficiencies, though benefits vary (12%-41%) depending on regional energy characteristics.

Lifecycle analysis indicates operational energy consumption accounts for 68% of total emissions, with 32% attributed to embodied carbon, emphasizing the importance of comprehensive lifecycle approaches. Temporal analysis identifies evolving emission patterns, with storage systems increasing their proportional contribution by 8.3 percentage points over the past decade while printing systems declined by 6.1 percentage points, reflecting transitions toward digital workflows and expanded analytics capabilities. As shown in Table 1, the digital maturity index serves as a critical indicator of organizational capability to implement carbon-efficient information management practices, with enterprises demonstrating higher digital maturity consistently exhibiting lower emission intensities across sectors, supporting digital transformation as a foundational pathway toward carbon neutrality.

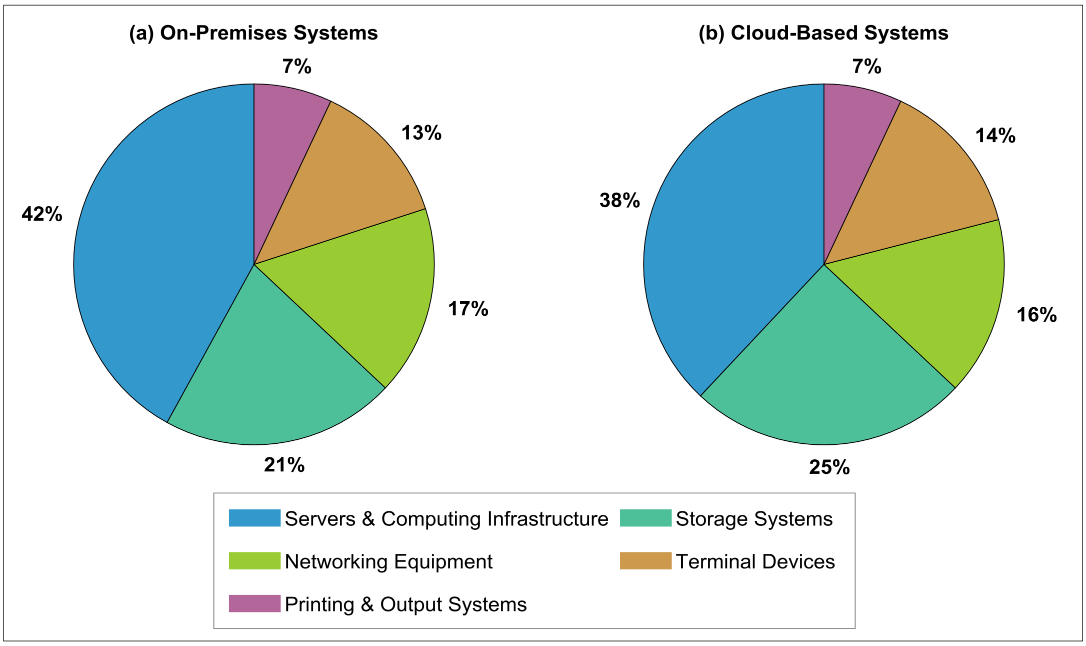

Figure 3. Carbon emission distribution across information system components

Table 1. Comparison of carbon emission characteristics across different enterprise information systems

Enterprise Type	Annual Carbon Emissions (tCO_2e)	Emission Intensity ($kgCO_2e/TB$)	Primary Emission Sources	Energy Efficiency Measures	Digital Maturity Index
Financial Institutions	7,850 - 12,400	152 - 275	Data centers (65%), Client devices (18%), Network infrastructure (12%)	Server virtualization, Dynamic cooling systems	3.8/5.0
Manufacturing Enterprises	4,200 - 8,600	95 - 187	OT systems (52%), Enterprise applications (28%), Client devices (15%)	Equipment upgrades, Green procurement policies	2.9/5.0
Retail Organizations	3,100 - 5,800	108 - 196	Point of sale systems (32%), Data centers (29%), Network infrastructure (26%)	Cloud migration, Energy management software	3.2/5.0
Technology Companies	5,400 - 9,800	74 - 125	Software development environments (42%), Data centers (37%), Testing infrastructure (18%)	Renewable energy, Advanced cooling technologies	4.6/5.0
Healthcare Providers	3,900 - 7,200	136 - 242	Electronic health records (38%), Imaging systems (25%), Administrative systems (24%)	Device consolidation, Smart building integration	3.0/5.0
Public Sector Agencies	4,800 - 8,900	128 - 215	Administrative systems (35%), Public service platforms (32%), Legacy systems (27%)	Centralized IT services, Equipment lifecycle management	2.5/5.0

Note: Emission intensity is calculated as carbon emissions per terabyte of data processed; Digital Maturity Index evaluates the organizational adoption of digital technologies on a scale of 1.0 to 5.0

3.2. Multi-Level Optimization Path of Green Business Information Management System

3.2.1. Information Infrastructure Layer Optimization Paths

Information infrastructure constitutes the foundation of business information management systems and represents a critical intervention point for carbon neutrality transformations. Comprehensive analysis reveals multiple optimization pathways with varying carbon reduction potentials and implementation complexities. Server consolidation and virtualization emerge as primary approaches, delivering carbon reductions of 25-38% through improved utilization rates and reduced hardware requirements, with organizations achieving average PUE improvements from 2.1 to 1.4. Storage optimization through tiered architectures demonstrates 18-23% energy efficiency improvements by aligning storage performance characteristics with data access patterns and retention requirements.

Energy-efficient hardware procurement delivers consistent carbon reductions across organizational contexts. As illustrated in Figure 4(a), the carbon abatement potential of energy-efficient servers increases substantially with implementation scale, achieving 31-42% emissions reductions in enterprise-wide deployments compared to baseline scenarios. This non-linear relationship highlights the importance of comprehensive implementation approaches. Infrastructure refresh cycles significantly impact carbon reduction potential, with accelerated refresh strategies (3-4 years) delivering 15-22% greater carbon reductions compared to extended cycles due to rapid evolution of energy efficiency technologies.

Network infrastructure optimization through software-defined networking offers 12-18% efficiency improvements via dynamic resource allocation. As shown in Figure 4(b), SDN efficiency gains demonstrate strong sensitivity to workload variability, with highly variable traffic patterns achieving substantially greater benefits. Cooling infrastructure optimization represents another critical pathway, with advanced technologies delivering 28-35% efficiency improvements, while liquid cooling systems demonstrate 45-60% improvements in high-density computing environments. Renewable energy integration constitutes a transformative pathway, with direct procurement enabling 70-95% reductions in infrastructure carbon footprints, while on-site generation provides complementary benefits through improved resilience. As demonstrated in Figure 4, combined implementation of energy efficiency measures and renewable energy integration delivers carbon reduction potentials significantly exceeding those achieved through isolated interventions, underscoring the importance of holistic approaches addressing both supply-side and demand-side dimensions. The 32% embodied carbon component necessitates longer equipment retention periods, even when newer technologies offer superior efficiency.

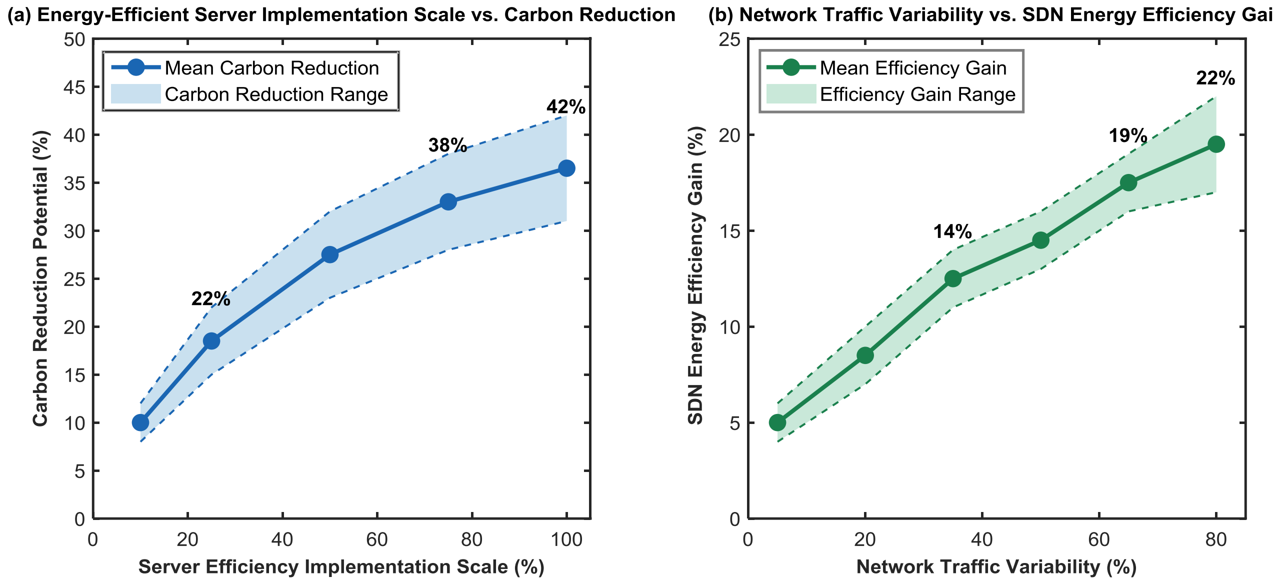

Figure 4. Information infrastructure, energy efficiency optimization and carbon reduction potential analysis

3.2.2. Data Management Layer Optimization Paths

The data management layer represents a critical intervention point for carbon neutrality initiatives within business information systems, offering substantial reduction potential through optimized storage, processing, and lifecycle management strategies. Data deduplication emerges as a foundational approach, with enterprise implementations achieving 27-38% storage reduction ratios and corresponding carbon emissions decreases of 21-29%. Organizations implementing comprehensive deduplication across primary storage, backup systems, and archives have demonstrated average electricity consumption reductions of 256-410 kWh per terabyte managed annually. Advanced deduplication technologies incorporating machine learning algorithms have further enhanced these benefits, achieving reduction ratios up to 45% in environments with highly repetitive data patterns.

Data compression technologies offer complementary optimization opportunities, with context-adaptive compression algorithms demonstrating 18-31% storage efficiency improvements. As shown in Table 2, columnar compression techniques for analytical databases have delivered particularly impressive results, with carbon footprint reductions of 24-36% achieved through reduced storage requirements and optimized I/O operations. The combination of deduplication and compression technologies demonstrates strong synergistic effects, with integrated implementations achieving carbon reductions 15-22% greater than the sum of individual interventions, highlighting the importance of coordinated optimization strategies.

Data lifecycle management represents another critical pathway with significant carbon reduction potential. Automated tiering solutions that dynamically allocate data across performance and capacity tiers based on access patterns have demonstrated energy efficiency improvements of 32-45% compared to traditional approaches. As illustrated in Table 2, lifecycle management strategies have shown particularly strong carbon reduction potential in regulated industries with substantial compliance-driven data retention requirements. Distributed data architectures leverage geographic distribution to reduce both carbon emissions and latency, with edge data processing frameworks demonstrating transmission volume reductions of 65-82% compared to centralized approaches. The integration of data management optimization with broader carbon neutrality initiatives requires carefully planned implementation strategies aligned with organizational characteristics and priorities. As shown in Table 2, the selection of optimal pathways demonstrates significant sensitivity to factors including data growth rates, access patterns, regulatory requirements, and existing infrastructure characteristics.

Table 2. Data management optimization strategies and implementation matrix

Optimization Strategy	Carbon Reduction Potential	Implementation Complexity	Organizational Prerequisites	Recommended Implementation Phases	Primary Benefits
Data Deduplication	21-29%	Medium	Data visibility, Storage management maturity	Phase 1: Primary storage Phase 2: Backup systems Phase 3: Archives	Storage reduction, Backup efficiency, Energy savings
Advanced Compression	18-31%	Medium-High	Workload performance analysis, Data classification	Phase 1: Structured databases Phase 2: Unstructured content Phase 3: Real-time data	Storage efficiency, I/O reduction, Processing optimization
Information Lifecycle Management	35-52%	High	Data governance framework, Retention policies, Classification schema	Phase 1: Policy development Phase 2: Archive implementation Phase 3: Automated enforcement	Regulatory compliance, Storage optimization, Process efficiency
Automated Data Tiering	32-45%	Medium-High	Access pattern analysis, Performance monitoring	Phase 1: Static tiering Phase 2: Policy-based automation Phase 3: AI-driven optimization	Cost optimization, Performance improvement, Energy efficiency
Edge Data Processing	65-82%*	High	Distributed infrastructure, Edge capabilities	Phase 1: Edge filtering Phase 2: Local analytics Phase 3: Autonomous operation	Transmission reduction, Latency improvement, Bandwidth optimization
Database Architecture Optimization	35-48%	High	Database expertise, Workload analysis	Phase 1: Query optimization Phase 2: Indexing strategies Phase 3: Database refactoring	Processing efficiency, Response time, Resource utilization
Data Locality Strategies	18-29%	Medium	Workload distribution analysis, Geographic data mapping	Phase 1: Access pattern analysis Phase 2: Geographic replication Phase 3: Dynamic optimization	Processing efficiency, Transmission reduction, Latency improvement

* Note: Reduction in data transmission volume rather than direct carbon footprint; overall carbon impact depends on network infrastructure characteristics and regional energy mix.

3.2.3. Business Application Layer Optimization Paths

The business application layer presents significant opportunities for carbon reduction through targeted optimization strategies that enhance both operational efficiency and environmental performance. Analysis reveals inefficient application architectures can contribute up to 35% of total information system emissions, underscoring the critical importance of application optimization in carbon neutrality initiatives. Application consolidation emerges as a primary optimization pathway, with comprehensive rationalization strategies achieving carbon footprint reductions of 28-42% through eliminated redundancies and improved resource utilization. As shown in Figure 5(a), carbon reduction potential demonstrates a non-linear relationship with consolidation ratio, with initial efforts yielding substantial benefits while marginal returns diminish as optimization progresses. Enterprise application integration frameworks have demonstrated additional carbon reductions of 15-22% by eliminating energy-intensive data transformation and synchronization processes.

The migration from monolithic to microservice architectures enables a business application optimization leap, offering a carbon efficiency improvement of 31% to 47%. Enhanced deployment flexibility, improved scalability, accuracy in resource allocation, and application component containerization are some reasons cited for this claim. The growing popularity of containerization has also provided these organizations an additional 18% to 26% efficiency due to reduced overheads and better resource utilization. As demonstrated in Figure 5(b), such design modifications have a remarkable potential for dynamic carbon reduction that can dramatically change depending on business context, workload fluctuation, and evolving needs verticals.

In the case of output energy, application code optimization can translate to an improvement of 22-35% because of more streamlined processing and minimizing computational waste. Static code analysis tools allow mitigation of targeted carbon output just-in-time during business operations. Transfiguration of Cloud-native applications provides the most comprehensive optimization pathway since such architecture transforms result in enhanced resource use, automation in scaling, and deployment of low carbon emitting infrastructure—leading to a 35-48% reduction in carbon footprint. The carbon-neutrality-oriented model for application disassembly and reconstitution sheds light on conquering optimization challenges while correlating Figure 5 posed to framework agility-contraction architecture-building complexity and carbon efficiency. The findings show that structural simplification leads to average emission reduction of 28 to 39% without compromising on functionalities.

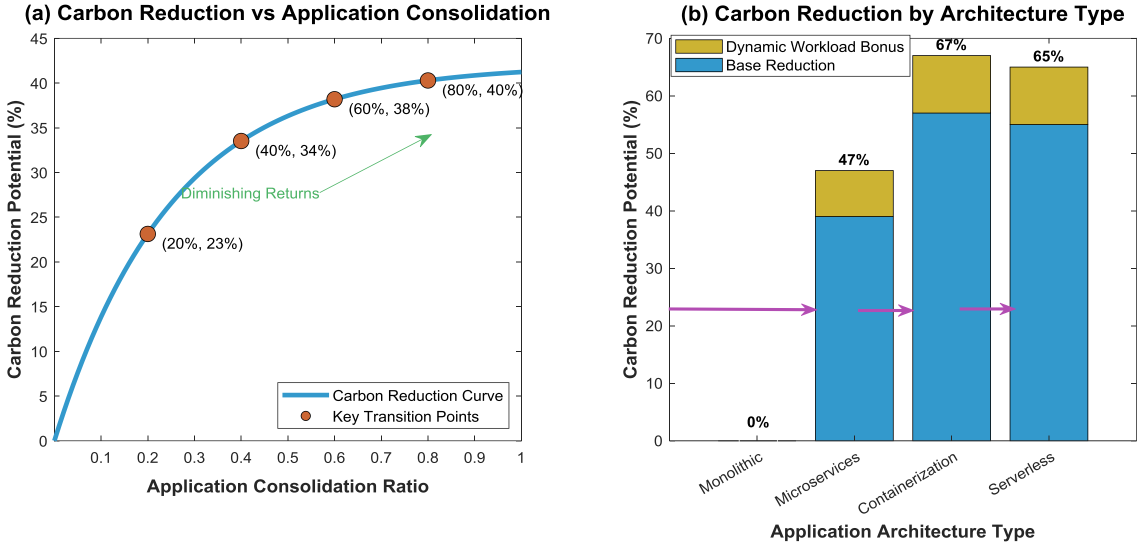

Figure 5. Carbon footprint-based application reconstruction model

3.3. Green Digital Transformation Path Benefit Assessment

The approaches to achieving green digital transformation add value in several aspects including ecological, economic, and operational, thereby through systematic undertaking strategies yielding substantial rewards to firms. Cross-sector assessments indicate that there is considerable impact from transformation efforts; on average, there is a 42.6% reduction in emissions. In tech companies, as shown in Figure 6(a), they lead the pack for reduction capability with an astonishing 68%, followed by financial institutions at 53%, and manufacturing enterprises at 41%. Temporal analysis identifies non-linear benefit accumulation patterns, with initial implementation phases delivering 15-20% reductions, while subsequent optimization stages achieve 35-45% incremental gains through synergistic integration. These environmental improvements strongly correlate with digital maturity indices (r=0.78), reinforcing the relationship between technological sophistication and carbon efficiency.

Economic assessment validates the business case for transformation initiatives, with programs delivering average ROI values of 132-278% over five-year periods. As detailed in Table 3, financial performance varies by sector, with payback periods ranging from 14 months in technology companies to 36 months in manufacturing enterprises. Operational expenditure reductions constitute the primary economic benefit (52%), complemented by enhanced resource utilization (27%) and infrastructure optimization (21%). Enterprise-wide implementations demonstrate 35% higher ROI compared to departmental initiatives, with 83% of assessed projects achieving positive risk-adjusted NPV under conservative scenarios, establishing the financial viability of comprehensive transformation approaches. These ROI calculations derive from cross-industry medians without accounting for regional variation. Local electricity markets, carbon policies, and infrastructure maturity significantly influence actual returns.

As illustrated in Figure 6(b), transformation initiatives generate substantial operational and strategic benefits beyond environmental improvements, including significant enhancements in system availability (28%), processing efficiency (43%), and infrastructure scalability (52%). Critical success factor analysis identifies organizational elements essential for effective implementation, with leadership commitment emerging as the primary determinant (correlation coefficient 0.74), followed by business strategy integration (0.68) and dedicated resources (0.62). The comprehensive assessment framework demonstrated in Figure 6 and detailed in Table 3 provides organizations with structured methodologies for evaluating transformation initiatives, underscoring the importance of holistic approaches that integrate carbon neutrality considerations with broader business value creation strategies.

Table 3. Green digital transformation project return on investment analysis

Industry Sector	Project Scale	Implementation Duration	Investment (USD)	Annual Carbon Reduction (tCO_2e)	5-Year ROI	Payback Period (months)	Primary Value Drivers
Technology	Enterprise	24 months	$1,850,000	4,250	278%	14	Energy cost reduction (42%), Operational efficiency (35%), Infrastructure optimization (23%)
Financial Services	Divisional	30 months	$2,650,000	5,700	215%	18	Compliance benefits (38%), Energy cost reduction (31%), Resource optimization (21%)
Manufacturing	Enterprise	36 months	$3,200,000	6,800	167%	26	Resource optimization (44%), Process efficiency (32%), Energy cost reduction (24%)
Healthcare	Departmental	18 months	$950,000	1,850	132%	22	Operational resilience (38%), Compliance benefits (33%), Energy cost reduction (29%)
Retail	Enterprise	28 months	$2,100,000	3,900	196%	20	Infrastructure optimization (41%), Energy cost reduction (36%), Customer experience (23%)
Public Sector	Divisional	32 months	$1,750,000	2,950	145%	36	Compliance benefits (47%), Resource optimization (32%), Energy cost reduction (21%)

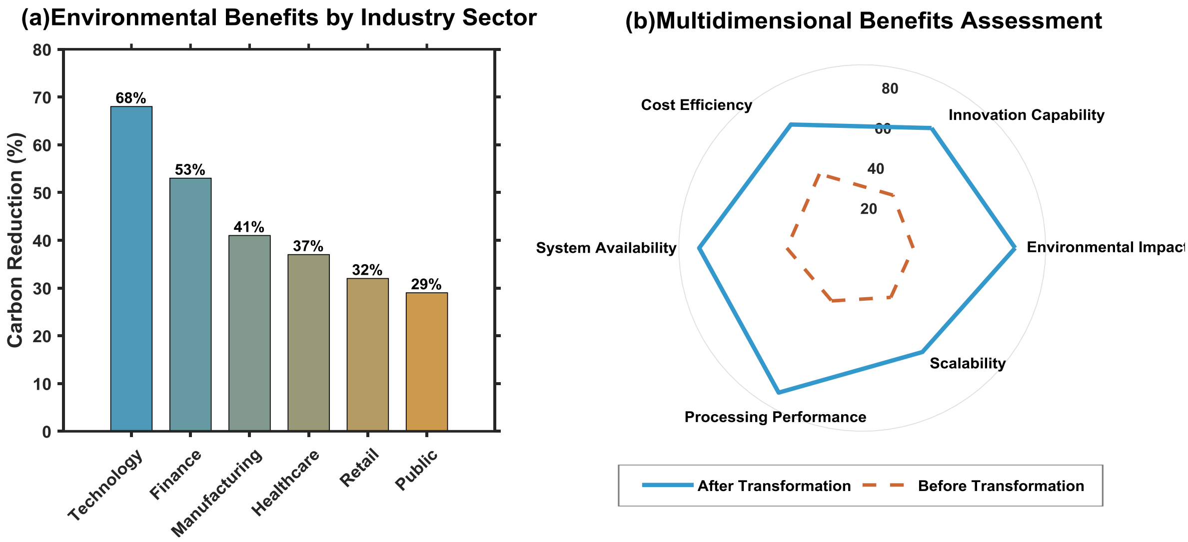

Figure 6. Green Digital transformation comprehensive benefit assessment

4. Discussion

The development of green information technology presents huge opportunities for organizations in their efforts to achieve carbon neutrality targets. As per the vast body of research carried out by Shang & Lv [33], adoption of green technologies in management systems that manage data presents huge potential, thus allowing data-based decision-making that maximizes resource allocation while minimizing ecological footprints. The deployment of digital platforms in carbon management has synergistic advantages that improve operational efficiency as well as environmental performance. Information systems have an important role to play by providing analytical tools that help in measuring, monitoring, and minimizing carbon emissions in organizational settings, effectively influencing the way firms define and pursue sustainability targets in their digital platforms. Our findings demonstrate this potential, with 42.6% emission reduction substantially exceeding the 15-25% range reported by Gholami et al. [14], reflecting advances in cloud adoption and measurement methodologies since 2013.

Data governance is known to play an important role in facilitating sustainable management practice. Sheng et al. [34] explore the role of digital transformation in managing low-carbon operations, noting that advances in organizational performance depend in large measure on efficient data governance models. Such models clearly define data acquisition, data assurance, and analytical processing rules, thus enabling carbon-based decision-making. Organizations with complete data governance approaches have more capabilities for emissions monitoring, compliance with regulations, and making sustainability reports, with data governance process advancements positively associated with carbon management effectiveness. This suggests that data accuracy, in this case, acts as a fundamental driver of environmental performance for firms undergoing digital transformation, thereby requiring sophisticated data management practices as a tactical prerequisite to achieving carbon neutrality.

Controlling the lifecycle of carbon-emission-related IT systems requires holistic coverage of emissions during the design, deployment, operational, and dismantling phases. Liu et al. [35] propose models tailored to carbon assets in digital decision-support systems that aid firms in calculating the ecological footprint of their IT investments throughout all business process cycles. This perspective reveals numerous opportunities for maximizing system architecture, deployment techniques, and operational processes. Notably, cloud-based architectures have shown considerable potential in reducing lifecycle emissions by streamlining resource allocation and enhancing energy efficiency. Furthermore, dynamic workload management techniques add to such benefits by optimizing computational resources to match available computational demands, minimizing idle capacity, as well as unnecessary energy consumption. However, efficiency improvements often trigger consumption increases that partially erode anticipated gains, while accelerated refresh cycles generate substantial embodied emissions and e-waste.

The development of green information management capabilities requires considerable investment in both technological infrastructure and human expertise. Jagger et al. [36] recognize skills challenges as key barriers to delivering low-carbon transitions, referring to the need to create specialist expertise that encompasses technical competencies such as energy-efficient system design and carbon analytics, as well as managerial competencies such as sustainability governance, stakeholder management, and stakeholder relations. The challenges that arise from efforts to implement carbon-neutral information management are complex mitigation strategies that address technical and organizational problems. Kannan et al. [37] analyze the implementation barriers, observing that information asymmetry and technological complexity materialize as key challenges, manifesting in turn as challenges related to emissions measurement, data integration across organizations, and deploying carbon-aware technologies. Mitigating these challenges requires solutions that cover technological advancements, organizational change management techniques, and strategic investments on the part of management to achieve a smooth transition to carbon-neutral information management systems. Looking ahead, emerging technologies offer promising pathways, with machine learning enabling dynamic energy optimization, blockchain providing transparent carbon tracking, and IoT infrastructure supporting granular emissions monitoring. These implementations require careful assessment of computational overhead relative to emission benefits.

5. Conclusion

This study creates an integrated framework to improve digital transformation trajectories in carbon-neutral green business information management systems. By systematic comparison of carbon footprints related to information systems in varying enterprise settings, this research establishes unique emission patterns that demonstrate high variability across differing sectors, operational sizes, and tech architectures. The finding of high-level negative correlation (r = -0.73) between digital maturity scores and intensity levels reveals that organizations that effectively execute digital transformation projects experience high carbon reduction rates, averaging 31% over five years. The developed process for optimized digital transformation in three tiers covers levels related to information infrastructure, data administration, and business application, allowing organizations to realize an average emission reduction of 42.6% due to overall transformation efforts, with tech companies realizing greatest reduction rates at 68%. Economic validation supports business value extracted from transformation efforts by showcasing average measures for return on investment (ROI) scores varying from 132% to 278% over five years. This research contributes to practice-based theory in information management by linking technological structure to ecological performance, thereby enhancing decision-support models for green digital transformation. The proposed quantification approach enables efficient measurement of operations-related as well as lifecycle-related emissions, creating necessary baselines for intervention, while implementation matrices offer domain-specific recommendations, enabling executable approaches to reducing carbon footprints while maintaining operations efficiency as well as business competitiveness. However, implementations must address challenges including rebound effects and embodied carbon from equipment refresh cycles. Future research should explore integration of emerging technologies such as machine learning, blockchain, and IoT while assessing their computational overhead against emission reduction benefits.

6. Declarations

6.1. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.2. Funding

The author received no financial support for the research, authorship, and/or publication of this article.

6.3. Institutional Review Board Statement

Not applicable.

6.4. Informed Consent Statement

Not applicable.

6.5. Declaration of Competing Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

7. References

[1] Singh, R. K., & Modgil, S. (2024). Impact of information system flexibility and dynamic capabilities in building net zero supply chains. Journal of Enterprise Information Management, 37(3), 993–1015. doi:10.1108/JEIM-09-2023-0477.

[2] Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. MIS Quarterly: Management Information Systems, 36(4), 1165–1188. doi:10.2307/41703503.

[3] Malhotra, A., Melville, N. P., & Watson, R. T. (2013). Spurring impactful research on information systems for environmental sustainability. MIS Quarterly: Management Information Systems, 37(4), 1265–1274. doi:10.25300/MISQ/2013/37:4.3.

[4] Zhang, Z., Hu, G., Mu, X., & Kong, L. (2022). From low carbon-to-carbon neutrality: A bibliometric analysis of the status, evolution and development trend. Journal of Environmental Management, 322, 116087. doi:10.1016/j.jenvman.2022.116087.

[5] Han, D., Li, M., & Lu, K. (2025). Digital platforms enabling carbon neutral technology innovation: based on market incentives and government constraints. Humanities and Social Sciences Communications, 12(1), 1–17. doi:10.1057/s41599-025-04691-5.

[6] Zhang, M., Liu, R., & Sun, H. (2025). Achieving carbon-neutral economies through circular economy, digitalization, and energy transition. Scientific Reports, 15(1), 13779. doi:10.1038/s41598-025-97810-w.

[7] Han, S., Zhang, H., Li, H., & Xun, Z. (2025). Digital transformation and carbon emission reduction: The moderating effect of external pressure and support. Journal of Cleaner Production, 500, 145108. doi:10.1016/j.jclepro.2025.145108.

[8] Pourhejazy, P., Wyciślak, S., Solvang, W. D., & Ericson, Å. (2025). Editorial: Supply chain transformation for pursuing carbon-neutrality. Frontiers in Sustainability, 6, 1548813. doi:10.3389/frsus.2025.1548813.

[9] Liao, H. T., Pan, C. L., & Zhang, Y. (2023). Smart digital platforms for carbon neutral management and services: Business models based on ITU standards for green digital transformation. Frontiers in Ecology and Evolution, 11, 1134381. doi:10.3389/fevo.2023.1134381.

[10] Sarkis, J., Koo, C., & Watson, R. T. (2013). Green information systems and technologies - This generation and beyond: Introduction to the special issue. Information Systems Frontiers, 15(5), 695–704. doi:10.1007/s10796-013-9454-5.

[11] Jałowiec, T., Wojtaszek, H., & Miciuła, I. (2022). Analysis of the Potential Management of the Low- Carbon Energy Transformation by 2050. Energies, 15(7), 2351. doi:10.3390/en15072351.

[12] Raja, S. P. (2021). Green Computing and Carbon Footprint Management in the IT Sectors. IEEE Transactions on Computational Social Systems, 8(5), 1172–1177. doi:10.1109/TCSS.2021.3076461.

[13] Slameršak, A., Kallis, G., & O'Neill, D. W. (2022). Energy requirements and carbon emissions for a low-carbon energy transition. Nature Communications, 13(1), 6932. doi:10.1038/s41467-022-33976-5.

[14] Gholami, R., Sulaiman, A. B., Ramayah, T., & Molla, A. (2013). Senior managers' perception on green information systems (IS) adoption and environmental performance: Results from a field survey. Information and Management, 50(7), 431–438. doi:10.1016/j.im.2013.01.004.

[15] Mat Nawi, M. N., Fauzi, M. A., Ting, I. W. K., Wider, W., & Amaka, G. B. (2025). Green information technology and green information systems: science mapping of present and future trends. Kybernetes, 54(6), 3136–3155. doi:10.1108/K-10-2023-2139.

[16] Zhao, G., Jiang, P., Zhang, H., Li, L., Ji, T., Mu, L., Lu, X., & Zhu, J. (2024). Mapping out the regional low-carbon and economic biomass supply chain by aligning geographic information systems and life cycle assessment models. Applied Energy, 369, 123599. doi:10.1016/j.apenergy.2024.123599.

[17] Wei, Y. M., Chen, K., Kang, J. N., Chen, W., Wang, X. Y., & Zhang, X. (2022). Policy and Management of Carbon Peaking and Carbon Neutrality: A Literature Review. Engineering, 14, 52–63. doi:10.1016/j.eng.2021.12.018.

[18] Huovila, A., Siikavirta, H., Antuña Rozado, C., Rökman, J., Tuominen, P., Paiho, S., Hedman, Å., & Ylén, P. (2022). Carbon-neutral cities: Critical review of theory and practice. Journal of Cleaner Production, 341, 130912. doi:10.1016/j.jclepro.2022.130912.

[19] Shaharudin, M. S., Fernando, Y., Chiappetta Jabbour, C. J., Sroufe, R., & Jasmi, M. F. A. (2019). Past, present, and future low carbon supply chain management: A content review using social network analysis. Journal of Cleaner Production, 218, 629–643. doi:10.1016/j.jclepro.2019.02.016.

[20] Guan, Z., Zhao, Y., & Wang, X. (2022). Design pragmatic method to low-carbon economy visualisation in enterprise systems based on big data. Enterprise Information Systems, 16(8–9), 1898049. doi:10.1080/17517575.2021.1898049.

[21] Dalene, F. (2012). Technology and information management for low-carbon building. Journal of Renewable and Sustainable Energy, 4(4), 041402. doi:10.1063/1.3694120.

[22] Dias, A. C., & Arroja, L. (2012). Comparison of methodologies for estimating the carbon footprint-case study of office paper. Journal of Cleaner Production, 24, 30–35. doi:10.1016/j.jclepro.2011.11.005.

[23] Li, Y., Yang, X., Du, E., Liu, Y., Zhang, S., Yang, C., Zhang, N., & Liu, C. (2024). A review on carbon emission accounting approaches for the electricity power industry. Applied Energy, 359, 122681. doi:10.1016/j.apenergy.2024.122681.

[24] Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E., & Weidema, B. (2016). The ecoinvent database version 3 (part I): overview and methodology. International Journal of Life Cycle Assessment, 21(9), 1218–1230. doi:10.1007/s11367-016-1087-8.

[25] Uddin, M., Darabidarabkhani, Y., Shah, A., & Memon, J. (2015). Evaluating power efficient algorithms for efficiency and carbon emissions in cloud data centers: A review. Renewable and Sustainable Energy Reviews, 51, 1553–1563. doi:10.1016/j.rser.2015.07.061.

[26] Yang, J., Zheng, C., & Liu, H. (2022). Digital Transformation and Rule of Law Based on Peak CO2 Emissions and Carbon Neutrality. Sustainability (Switzerland), 14(12), 7487. doi:10.3390/su14127487.

[27] Zampou, E., Mourtos, I., Pramatari, K., & Seidel, S. (2022). A Design Theory for Energy and Carbon Management Systems in the Supply Chain. Journal of the Association for Information Systems, 23(1), 329–371. doi:10.17705/1jais.00725.

[28] Golden, B. L., Wasil, E. A., & Harker, P. T. (1989). The analytic hierarchy process. Applications and Studies, Berlin, Germany. doi:10.1007/978-3-642-50244-6.

[29] Yao, H., Xu, P., Wang, Y., & Chen, R. (2023). Exploring the low-carbon transition pathway of China’s construction industry under carbon-neutral target: A socio-technical system transition theory perspective. Journal of Environmental Management, 327, 116879. doi:10.1016/j.jenvman.2022.116879.

[30] Bhatia, M., Meenakshi, N., Kaur, P., & Dhir, A. (2024). Digital technologies and carbon neutrality goals: An in-depth investigation of drivers, barriers, and risk mitigation strategies. Journal of Cleaner Production, 451, 141946. doi:10.1016/j.jclepro.2024.141946.

[31] He, B., Yuan, X., Qian, S., & Li, B. (2023). Carbon neutrality: a review. Journal of Computing and Information Science in Engineering, 23(6), 060809. doi:10.1115/1.4062545.

[32] Mao, J., Yuan, H., Xiong, L., & Huang, B. (2024). Research Review of Green Building Rating System under the Background of Carbon Peak and Carbon Neutrality. Buildings, 14(5), 1257. doi:10.3390/buildings14051257.

[33] Shang, W. L., & Lv, Z. (2023). Low carbon technology for carbon neutrality in sustainable cities: A survey. Sustainable Cities and Society, 92, 104489. doi:10.1016/j.scs.2023.104489.

[34] Sheng, H., Feng, T., & Liu, L. (2023). The influence of digital transformation on low-carbon operations management practices and performance: does CEO ambivalence matter? International Journal of Production Research, 61(18), 6215–6229. doi:10.1080/00207543.2022.2088426.

[35] Liu, Y., Tian, L., Sun, H., Zhang, X., & Kong, C. (2022). Option pricing of carbon asset and its application in digital decision-making of carbon asset. Applied Energy, 310, 118375. doi:10.1016/j.apenergy.2021.118375.

[36] Jagger, N., Foxon, T., & Gouldson, A. (2013). Skills constraints and the low carbon transition. Climate Policy, 13(1), 43–57. doi:10.1080/14693062.2012.709079.

[37] Kannan, D., Solanki, R., Kaul, A., & Jha, P. C. (2022). Barrier analysis for carbon regulatory environmental policies implementation in manufacturing supply chains to achieve zero carbon. Journal of Cleaner Production, 358, 131910. doi:10.1016/j.jclepro.2022.131910.