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Embedding Sustainability into Data Practices for Digital Transformation: A Systematic Review

Wattana Viriyasitavat[1], Ra-pee Pattanapanyasat[2], Danupol Hoonsopon[3], Phoranee Rhuwadhana[4], Nuttirudee Charoenruk[5], Vitara Pungpapong[6]

Abstract

This study advocates a "Sustainable-by-Design" approach that embeds sustainability throughout the data lifecycle—from collection to disposal—within digital transformation (DT). Based on a systematic literature review of 55 peer-reviewed articles (2006–March 2025), and guided by Dynamic Capabilities Theory, RBV/NRBV, and Institutional Theory, the paper identifies seven key enablers: Sustainable Data Analytics and AI, Strategy Alignment, Organizational Capabilities, Infrastructure, ESG Governance, Data Design, and Institutional Pressures. These are synthesized into a three-stage maturity model—Foundational, Integrated, and Transformative. Findings highlight a focus on internal capabilities while institutional forces remain underexplored. The study contributes a multi-theoretical framework and offers practical guidance for embedding ESG principles into data governance, promoting responsible and regenerative DT.

Keywords: *Digital Transformation, Sustainability, Dynamic Capabilities Theory, Resource-Based and Natural Resource-Based Views.*

Introduction

Digital transformation (DT) dominates strategic agendas, yet the data volumes that power this shift are expanding at an unprecedented pace: IDC's Worldwide Global DataSphere Forecast 2021–2025 projects that global data creation and replication will exceed 180 zettabytes by 2025 (*Worldwide Global StorageSphere Forecast, 2022–2026: An Installed Base of 7.9ZB of Storage Capacity in 2021 Came at a Cost of $370 Billion — Is It Enough?*, n.d.) Rising data intensity magnifies both the energy required to store, process, and transport information and the social-ethical stakes of data governance. A recent analysis estimates that European data-center electricity demand could surge tripling current consumption and approaching 5 percent of Europe's total power use (Ascott, 2024). Industry leaders are reacting: Microsoft has pledged to become carbon negative by 2030 and to shift to 100 percent supply of renewable energy by 2025 (Smith, 2020). These developments crystallize an urgent managerial question: How can organizations embed sustainability principles into the very data practices that underpin their digital-transformation journeys?

[1] Chulalongkorn Business School, Chulalongkorn University Bangkok, Thailand, Email: hardgolf@gmail.com
[2] Chulalongkorn Business School, Chulalongkorn University Bangkok, Thailand, Email: ra-pee@cbs.chula.ac.th
[3] Chulalongkorn Business School, Chulalongkorn University Bangkok, Thailand, Email: danupol@cbs.chula.ac.th, (Corresponding Author)
[4] Technopreneurship and Innovation Management Program, Chulalongkorn University Bangkok, Thailand, Email: 6581028320@student.chula.ac.th
[5] Chulalongkorn Business School, Chulalongkorn University Bangkok, Thailand, Email: nuttirudee@cbs.chula.ac.th
[6] Chulalongkorn Business School, Chulalongkorn University Bangkok, Thailand, Email: vitara@cbs.chula.ac.th

Academic inquiry into sustainability within DT reflects two distinct perspectives.

Perspective A: Sustainable-by-Design Digital Transformation: *This perspective refers to the integration of sustainability principles directly into the processes, structures, and practices of DT itself. This perspective emphasizes a proactive, embedded approach in which Environmental, Social, and Governance (ESG) considerations are operationalized across the entire DT life cycle—ranging from data governance and system design to implementation and evaluation. It prioritizes the internal sustainability of DT, viewing sustainability not as an outcome, but as a design principle central to transformation initiatives* (Cui, 2025; Ferrari et al., 2022).

Perspective B: Outcome-Oriented Digital Transformation for Sustainability: *This perspective conceptualizes DT as a tool or enabler for achieving broader sustainability objectives. It focuses on the external impacts of digital initiatives—such as improvements in ESG performance, operational efficiency, or long-term organizational viability. Within this perspective, sustainability is treated as a desirable consequence of DT, rather than a guiding principle embedded within its core processes* (Albino et al., 2020; Vial, 2019).

Early work in the field, aligned with Perspective A, primarily concentrated on infrastructure efficiency and energy-aware architectures under the banner of green IT (Melville, 2010; Watson et al., 2010). However, integrated approaches that consider how organizations can proactively make their DT efforts sustainable—i.e., Perspective A—remain comparatively underdeveloped in the literature. Relatively few studies examine how to make DT itself sustainable by integrating environmental and social considerations throughout the data life-cycle (Gupta et al., 2024). Even comprehensive reviews by Feroz et al., 2021 (Feroz et al., 2021) devote limited attention to the organizational enablers—leadership commitment, cross-functional governance, incentive structures, and capability-building programs—that operationalize sustainable data practices. Consequently, scholars and practitioners lack an evidence-based roadmap for embedding sustainability into data-centric DT initiatives.

To structure our inquiry, we adopt the Digital Transformation Framework of Westerman et al (Westerman et al., 2014), Hess et al. (Hess et al., 2016) and (Tangwaragorn et al., n.d.), which distinguishes three domains—Digital, Organization, and External Environment. Within the Digital Domain, Digital Resources comprise *Data* and *Digital Infrastructure*. Given our objective to examine organizational enablers rather than technical efficiencies, this systematic review focuses exclusively on the Data construct of Digital Resources and deliberately excludes infrastructure-centric studies. Coverage is further restricted to peer-reviewed articles published between 2006 and 2025 (March), a period marked by accelerating discourse on both sustainability and DT.

Our analysis rests on three complementary theories that foreground organizational mechanisms:

1. *Dynamic Capabilities Theory (DCT)* explains how firms sense sustainability challenges, seize data-driven eco-efficient opportunities, and reconfigure processes to remain resilient (Eisenhardt & Martin, 2000; Teece et al., 1997).

2. *Resource-Based and Natural Resource-Based Views (RBV/NRBV)* conceptualize sustainable data practices as rare, valuable, and inimitable capabilities that not only confer long-term competitive advantage but also generate enduring environmental and social value through pollution prevention, product stewardship, and clean technology innovation (Barney, 1991; Hart, 1995).

3. *Institutional Theory* highlights how coercive, normative, and mimetic pressures spur adoption of sustainable data governance (DiMaggio & Powell, 1983).

Alternative frameworks, such as the Technology–Organization–Environment (TOE) model (Tornatzky & Fleischer, 1990) and Stakeholder Theory (Arnstein, 1969) are recognized in our findings but do not serve as coding lenses.

Accordingly, we conduct a Systematic Literature Review (SLR) that evaluates each article's treatment of Perspective A within the *Data* construct of Digital Resources. Our study addresses three research questions:

- RQ1: What organizational enablers are for embedding sustainability principles into data-related DT initiatives?
- RQ2: How extensively do existing studies employ DCT, RBV/NRBV, and Institutional Theory when analyzing sustainable data practices?
- RQ3: Where do theoretical and empirical gaps remain, and what future research directions are needed to advance sustainable data-resource practices?

Adopting the Reflexive Thematic Analysis approach by Braun & Clarke (Braun & Clarke, 2006), we began by conducting iterative coding of each article to understand how the authors make meaning of sustainability within data-life-cycle activities and how they portray the organizational enablers that support those practices. These qualitative codes were constantly compared and refined into higher-order themes that resonated—yet were not restricted by—established theory. We then translated the richness of these thematic insights that captures (a) the explicitness and breadth with which sustainability principles are woven through the data life-cycle and (b) the depth and reflexivity of each study's discussion of organizational enablers. Finally, the emergent themes and their respective scores were mapped onto constructs from DCT, RBV/NRBV, and Institutional Theory, yielding a transparent, theory-informed evidence matrix that preserves contextual nuance while enabling structured comparison across the literature.

This review furnishes three principal contributions. First, it sharpens the conceptual boundaries of sustainable DT by foregrounding the integration of sustainability across the data life-cycle, thus addressing an under-examined facet of the literature. Second, it synthesizes relevant theories into a unified framework, thereby revealing theoretical blind spots and establishing a multilevel foundation for future inquiry. Finally, it translates the evidence into a set of actionable organizational enablers providing practitioners with empirically grounded guidance for embedding sustainability within data-centric transformation initiatives.

The paper is structured as follows. Section 2 situates the study within the extant body of systematic reviews on sustainable digital transformation. Section 3 delineates the SLR methodology, detailing article retrieval, inclusion–exclusion criteria, and the theory-informed coding scheme. Section 4 reports the descriptive results of the review corpus. Section 5 analyses the emergent themes through the lenses of DCT, RBV/NRBV, and Institutional Theory, and elaborates on managerial implications and future research priorities. Section 6 summarizes the principal insights, acknowledges limitations, and outlines directions for subsequent investigation.

Existing Surveys on Digital Transformation and Sustainability

Over the past few years, a growing body of literature has examined the intersection of DT and sustainability across diverse organizational and industry contexts. Collectively, these studies highlight various aspects of sustainable DT, from smart cities to business model innovation and governance frameworks. However, while they address important dimensions of sustainability in digital contexts, they largely overlook the specific organizational enablers required for embedding sustainability principles into data resource practices throughout the transformation journey. Most studies either focus on Perspective B–examining the outcomes of DT on sustainability performance–or offer only partial insights into Perspective A–how sustainability principles can be embedded directly into DT processes themselves. Furthermore, a significant gap remains in research specifically addressing data-centric sustainability practices (See Table I).

Feroz et al. (Feroz et al., 2021) apply a science mapping approach to examine the link between DT and sustainability, finding that technologies, such as Big Data, Internet of Things (IoT), and AI can support sustainability goals and promote green business innovation. Their conceptualization of DT as a process that enhances efficiency through resource conservation and digital operations aligns largely with Perspective B, where DT acts as a tool to achieve external sustainability outcomes. Although they acknowledge environmental risks—such as high energy consumption in data centers—and propose technological fixes like green IT infrastructure, their analysis does not embed sustainability principles within the DT process itself. Furthermore, their discussion on organizational enablers and data practices remains high-level, with limited attention to responsible data governance or sustainable data lifecycle management.

Building on this instrumental view of DT, Nyagadza (Nyagadza, 2022) conducts a review grounded in Business Model Theory (BMT) to investigate sustainable DT in digital marketing firms, emphasizing digital agility and ambidexterity as drivers of long-term competitiveness. While the study repeatedly mentions sustainability, it primary focus is on business resilience and growth, hence reiterating Perspective B. Technologies are discussed within the Social, Mobile, Analytics, Cloud, and Internet of Things (SMACIT) framework, and big data is recognized as a transformation driver. However, there is little engagement with sustainability in data management, and organizational enablers are framed more as mechanisms to improve innovation performance than to embed sustainability within DT practices.

This emphasis on leveraging DT to enhance business adaptability continues in the work of Mangalaraj et al., (Mangalaraj et al., 2023) who explore the role of digital capabilities and dynamic capabilities in fostering organizational resilience across diverse settings, such as SMEs and industries disrupted by the COVID-19 pandemic. Their analysis further reinforces Perspective B, portraying DT as a response to external shocks rather than as a vehicle for embedding sustainability principles into core operations. However, sustainable data practices, such as ethical data handling or environmentally conscious storage remain absent. Organizational enablers are considered in terms of general adaptability, not specifically sustainability-oriented governance.

A similar orientation is found in the study by Sagala and Őri (Sagala & Őri, 2024), who construct a DT strategy framework to help SMEs transition from resilience to antifragility in volatile environments. While their work expands on the need for deeper organizational learning and stronger digital capability, the goal remains the strengthening of internal robustness and long-term viability. The discussion does not extend to sustainable data lifecycle management or policies for responsible data use. Sustainability is acknowledged only briefly, as a future area of interest rather than an integrated design principle.

The conceptual work of Dupin et al. (Dupin et al., 2023) focuses on clarifying the notion of digital resilience. Their multi-level framework outlines resilience across IT infrastructure, users, and organizational systems, predominantly from the standpoint of withstanding or adapting to technological disruptions. The prevailing *resilience through digital* perspective places digital technologies as enablers of system adaptation, situating the analysis within Perspective B. However, the work does not address the sustainability of data resources or ethical considerations in their governance. Even in discussions of Digital Public Infrastructure (DPI) for fragile states, the emphasis is on service continuity and coordination, not ecological or social sustainability.

Lastly, Hokmabadi et al. (Hokmabadi et al., 2024) contribute to this trend of how SMEs and startups use digital marketing capabilities to achieve business resilience. The role of data analytics is central, with data framed as a resource to optimize decision-making and marketing performance. However, as with other studies, sustainability is treated peripherally—mainly as a potential co-benefit of digital adoption—placing the paper firmly within Perspective B. Although organizational enablers, such as digital skill development and cyber risk management, are discussed, these are not directly linked to sustainable data governance or practices. Overall, this work reveals a consistent pattern: DT is largely treated as a means to drive resilience, competitiveness, and operational efficiency, with limited attention to how sustainability can be proactively embedded in the transformation process, particularly in relation to data resource practices.

The reviewed literature provides insights into the intersection of DT, organizational adaptation, and resilience. Collectively, these studies affirm DT's transformative potential and highlight the importance of organizational capabilities in managing complexity and uncertainty. However, a critical synthesis reveals a prevailing emphasis on Perspective B—positioning DT as a means to achieve external objectives such as sustainability, firm performance, adaptability, or public sector efficiency. This focus tends to obscure *Perspective A*, which addresses the internal sustainability of DT processes. In particular, sustainable data resource practices remain underexplored, despite the centrality of data to DT. While infrastructure concerns like green data centers are noted, broader issues are largely neglected. Moreover, the literature rarely identifies specific organizational enablers needed to institutionalize sustainable data practices. This gap suggests a disconnect. While DT's environmental and social impacts are sometimes acknowledged, the internal sustainability of transformation—particularly in relation to responsible data management—remains insufficiently addressed in current organizational research.

Articles	**Topic**	**Descriptions**	**Analysis**
(Feroz et al., 2021)	Digital transformation and environmental sustainability: A review and research agenda	Uses science mapping to show DT (Big Data, IoT) correlation with sustainability agendas; discusses DT for green business and	Primarily focuses on DT outcomes (Perspective B) and mitigating negative impacts, rather than embedding sustainability within DT processes (Perspective A). Lacks depth on sustainable data practices beyond

		mitigating environmental impacts (e.g., green data centers).	infrastructure and specific organizational enablers for them.
(Nyagadza, 2022)	Sustainable digital transformation for ambidextrous digital firms: systematic literature review, meta-analysis and agenda for future research directions	SLR/Meta-analysis on SDT for ambidextrous digital marketing firms using BMT; discusses SDT building blocks, SMACIT, culture, and agility.[2]	"Sustainable" often implies business viability (Perspective B leaning). Limited focus on ecological/social sustainability within DT (Perspective A), sustainable data practices, or the specific organizational enablers required.[2]
(Mangalaraj et al., 2023)	Digital Transformation for Agility and Resilience: An Exploratory Study	Explores how DT, dynamic capabilities, and agility enhance business resilience and firm sustainability (viability), often in response to disruptions like the pandemic or within SMEs.[4]	Overwhelmingly focuses on resilience outcomes (Perspective B). Does not address embedding sustainability within DT processes (Perspective A), sustainable data practices, or the specific organizational enablers needed for sustainable data management.[4]
(Sagala & Őri, 2024)	Exploring digital transformation strategy to achieve SMEs resilience and antifragility: a systematic literature review	SLR proposing a DT strategy framework (based on dynamic/digital capabilities, learning) for SME resilience and antifragility.[8]	Focuses on resilience/antifragility outcomes (Perspective B). Does not embed sustainability within DT processes (Perspective A) or address sustainable data practices. Discusses enablers only for resilience, not sustainable data management.[8]
(Dupin et al., 2022)	A Systematic Literature Review on Digital Resilience in Organizations: Towards a Conceptualization	SLR clarifying Digital Resilience (DR) concepts, distinguishing levels (user, IT infra, wider systems) and perspectives (through/to digital).[9]	Focuses on the concept of resilience, not sustainability (Perspective B alignment). Does not address embedding sustainability within DT (Perspective A), sustainable data practices, or their specific organizational enablers.[10]
(Hokmabadi et al., 2024)	Business Resilience for Small and Medium	SLR examining how DT and marketing capabilities	Clearly focuses on resilience outcomes (Perspective B). Sustainability discussed

	Enterprises and Startups by Digital Transformation and the Role of Marketing Capabilities: A Systematic Review	(analytics, digital tools) enhance business resilience in SMEs/startups.[11]	superficially or as an outcome. Lacks focus on embedding sustainability (Perspective A), sustainable data practices beyond marketing analytics, and specific organizational enablers for sustainable data management.

Table 1: Existing Surveys Related to DT and Sustainability

Research Methodology

This review employs an SLR design, drawing on Snyder's synthesis framework (Snyder, 2019), and further informed by the management-oriented guidance of Tranfield, Denyer, and Smart (Tranfield et al., 2003) to integrate wide-ranging perspectives on sustainability initiatives and stakeholder alignment. The SLR allows for a holistic appraisal that spans multiple theoretical lenses and methodological traditions. To reinforce transparency and replicability, the review is conducted in accordance with the 2020 update of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (Page et al., 2021), which collectively steers the systematic identification, appraisal, and synthesis of relevant studies. Adhering to these protocols ensures that insights on sustainability and stakeholder collaboration are consolidated within a clear, auditable process, summarized in Figure 1. Guided by established SLR procedures and the PRISMA framework, the study advances through a three-phase sequence—planning, execution, and reporting—outlined in the following sections.

Question formulation

Developing well-defined research questions is a foundational step in conducting an SLR, as it establishes analytical boundaries, ensures methodological alignment, and directs the synthesis process (Archibald, 2020). Following PRISMA guidelines and an initial scoping review of 55 peer-reviewed articles, the research team refined the review's focus through iterative discussion to address a critical gap in the literature: the limited attention to how sustainability principles are embedded within data-related aspects of DT—a view we term Perspective A. Most prior studies predominantly adopt *Perspective B*, treating DT as a vehicle for achieving external sustainability outcomes. While valuable, this instrumental lens often overlooks the internal sustainability of DT processes, particularly regarding the management and governance of data resources. Despite data being central to DT, there remains a notable lack of inquiry into how organizations govern data responsibly across its lifecycle. In particular, the literature provides limited guidance on the specific organizational enablers needed to institutionalize sustainable data practices. These insights guided the development of three research questions outlined in the Introduction section. By explicitly foregrounding, the study establishes a coherent framework for synthesizing evidence and advancing an integrative model of sustainable DT.

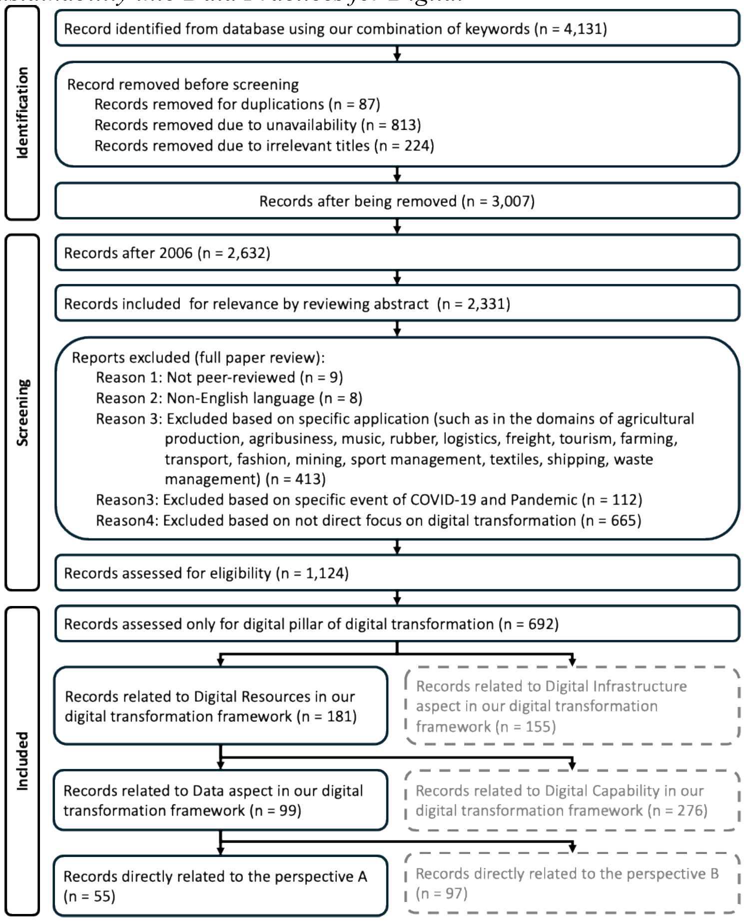

Figure 1. Research Methodology.

Article Selection Protocol

To ensure comprehensive and methodologically rigorous coverage of the relevant literature, a structured and reproducible search strategy was implemented across multiple leading academic databases, including Scopus, Web of Science, IEEE Xplore, Semantic Scholar, and Google Scholar. Additionally, targeted searches were conducted within ACM Digital Library, ScienceDirect (Elsevier), SpringerLink, SSRN, arXiv, and HAL, with inclusion limited to publications that met strict scholarly quality criteria. The review focused exclusively on peer-reviewed journal articles and high-quality conference proceedings published between 2006 and 2025 (March), a period marked by heightened scholarly interest in sustainability-oriented digital transformation. Studies featuring case-based analyses, particularly in the context of DT within supply chains and organizational governance, were prioritized where relevant.

The search was based on two principal keyword categories—Sustainability and DT—as detailed in Table II. Boolean operators (AND/OR), truncation (*), and phrase matching were employed to generate database-specific queries. This query structure was adapted to meet the syntax requirements of other databases. The focus was placed on retrieving articles that explicitly discussed sustainability within DT processes, rather than those merely exploring DT as a tool for achieving sustainability outcomes.

To strengthen completeness, a snowballing approach was also applied—examining citations and references within key articles to locate additional works. Only peer-reviewed journal articles and reputable conference papers were included, while grey literature, editorial content, and non-scholarly pieces were excluded to ensure academic quality. A seven-step filtering process was adopted in line with Tranfield et al. (Tranfield et al., 2003) and PRISMA guidelines (Jones et al., 2011):

1. Initial retrieval using the Table II keyword structure.
2. Deduplication of records across databases.
3. Title and abstract screening based on relevance to embedding sustainability within digital transformation.
4. Full-text accessibility and quality check.
5. Application of inclusion criteria—focus on data-centric sustainability practices.
6. Exclusion criteria—removal of papers focused solely on external ESG/SDG impacts (Perspective B).
7. Expert validation, where three domain experts independently reviewed and scored for alignment with the study's focus on organizational enablers of sustainable data practices (Perspective A).

This resulted in a final dataset of 55 rigorously selected articles. These were analyzed using a Reflexive Thematic Analysis framework, with the goal of identifying thematic insights on how sustainability principles are operationalized within DT, particularly through responsible data lifecycle management and organizational enablers.

Sustainability-related		**Digital Transformation-related**
Sustainability		Digital Transformation
ESG OR (Environment Social Governance)		Digitalization
SDG(s) OR (Sustainable Development Goals)		Digitization
Sustainable + (Development, Innovation, Growth)	AND	Digital Innovation
CSR OR (Corporate Social Responsibility)		Technology Transformation
Climate		IT Transformation
Green		Business Transformation
Carbon		
Circular Economy		
Net Zero		

Table 2: Search Keywords

Extraction, Analysis and Synthesis

To analyze the final set of studies, we adopted a dual-method approach (Gioia et al., 2013), combining descriptive analysis and reflexive thematic analysis. The descriptive component was used to map publication patterns across journals, years, and institutional affiliations, offering context on how scholarly attention to sustainable DT—particularly organizational enablers for sustainable data practices—has evolved over time. To investigate deeper conceptual trends, we applied a reflexive thematic analysis guided by established qualitative procedures (Ben Slimane et al., 2022), drawing on Wolcott's interpretive process (Wolcott, 1994) and Creswell and Poth's methodological design (Creswell & Poth, 2016). The analysis unfolded in four iterative stages:

Initial Familiarization and Scoping: We conducted a reading to extract content related to sustainability in data management and related ones, including governance structures, leadership engagement, ethical use, and organizational alignment. This enabled us to surface preliminary ideas and assess the conceptual boundaries of the studies.

Inductive and Theory-Informed Coding: Using both open coding and deductive coding aligned with DCT, RBV/NRBV, and Institutional Theory, we developed a coding scheme that captured recurring organizational enablers and data governance and other related mechanisms. Coding was conducted iteratively by three experts independently, with discrepancies resolved through discussion to enhance reliability.

Theme Construction and Framework Development: Refined codes were grouped into higher-order themes reflecting how sustainability principles are embedded in data-centric DT. These themes were used to construct an integrative framework illustrating key categories such as strategic drivers, enabling structures, decision-making processes, and cultural facilitators. The framework integrates insights to support future scholarly exploration and organizational design.

Visual Mapping and Interpretation: The final themes and their interrelationships were represented visually as our integrative framework to demonstrate the interaction between sustainability enablers and data aspects across organizational levels. These figures served not only to summarize findings but also to support theory-informed interpretation and comparison across studies.

This integrated analytic strategy allowed for both a contextual mapping of the literature and a deep thematic synthesis. The resulting framework contributes a structured, theory-driven understanding of how organizations can embed sustainability within data-driven digital transformation processes.

Thematic Coding and Theoretical Integration

To conduct a comprehensive analysis of the selected studies, this research utilized a reflexive thematic analysis approach, guided by the principles articulated by Braun and Clarke (Braun & Clarke, 2006, 2021) for qualitative synthesis. The central aim was to identify recurrent patterns pertaining to organizational enablers of sustainable data resource practices. Subsequently, these themes were interpreted through established theoretical lenses, enabling an exploration beyond superficial categorization to engage with the conceptual foundations of how sustainability is operationalized within data-driven DT.

A hybrid coding strategy integrating inductive (data-driven) and deductive (theory-informed) techniques was employed. Initially, each selected article was read thoroughly and open-coded for explicit and implicit references to organizational actions, strategies, or structures concerning the sustainability of data practices (e.g., data governance, capacity building, cultural alignment, technological infrastructure). These initial codes were subsequently refined and systematically organized into higher-order themes through an iterative process of constant comparison and collaborative discussion among the research team. To structure and enrich the interpretation of findings, emergent themes were mapped against three complementary theoretical frameworks, illustrated in Figure 2:

1. *Dynamic Capabilities Theory (DCT)* offered a lens to identify themes related to organizational responsiveness and adaptability. This included recognizing sustainability challenges (sensing), capitalizing on eco-efficient opportunities via data (seizing), and restructuring internal processes to align with long-term environmental and social objectives (reconfiguring), as conceptualized by Teece et al. (Teece et al., 1997) and further elaborated by Barreto (Barreto, 2010).

2. The *Resource-Based View (RBV)* and the *Natural Resource-Based View (NRBV)* guided the identification of sustainability practices functioning as strategic assets (Barney, 1991; Hart, 1995). In addition to highlighting valuable, rare, inimitable, and non-substitutable characteristics—such as ethical data cultures, energy-efficient analytics platforms, and specialized cross-functional sustainability knowledge—the NRBV lens further emphasizes how these practices contribute to pollution prevention, product stewardship, and clean technology development as pathways to both competitive and ecological advantage.

3. *Institutional Theory* provided the framework to analyze external pressures shaping sustainable data practices. This included coercive pressures like regulatory mandates (e.g., ESG disclosure requirements), normative expectations arising from industry standards, and mimetic influences, such as benchmarking against leading organizations (DiMaggio & Powell, 1983; Scott, 2001).

This triangulated theoretical approach facilitated a multi-dimensional understanding of each theme, encompassing both internal capability development and external institutional influences. The resultant coding framework served as the analytical basis for developing an integrative model. This model, detailed in Section 4, synthesizes the findings into a structured framework, thereby offering conceptual clarity and practical insights for embedding sustainability within data-centric DT initiatives.

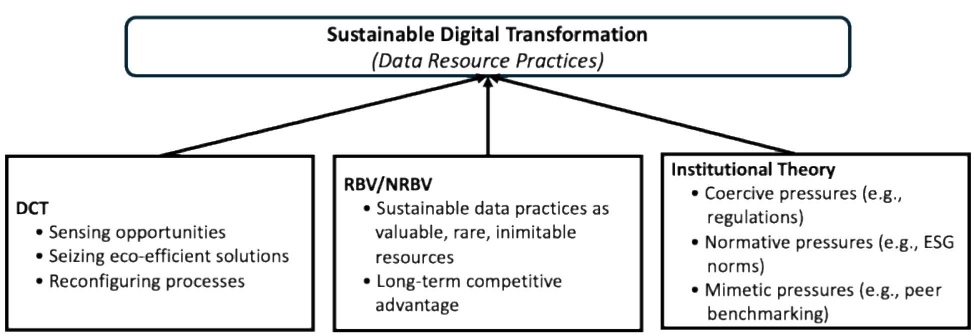

Figure 2. Theoretical Lenses for Interpreting Organizational Enablers of Sustainable DT in Data Resource Practices.

Reliability & Validity Procedures

To ensure methodological rigor and trustworthy findings from our reflexive thematic analysis, systematic procedures were implemented (Lincoln & Guba, 1985). These measures fostered coding consistency, managed researcher subjectivity through reflexivity (Watt, 2007), and strengthened interpretations via theoretical triangulation (Denzin, 1978), contributing to a robust methodological framework.

Enhancing Inter-Coder Reliability

Consistent data interpretation is crucial in qualitative analysis, and our inter-coder reliability assessment aimed to establish a shared understanding of the coding framework while minimizing idiosyncratic interpretations (Miles et al., 2020). The entire dataset of 55 studies was designated for independent coding by three research team members to assess inter-coder reliability. These team members, all familiar with the research questions and theoretical underpinnings, independently applied the preliminary coding scheme (derived from Section 3.3) to this entire dataset. Following this, coder concordance was quantitatively evaluated using percentage agreement (Miles & Huberman, 1994). A target reliability threshold of >80% agreement was set. The initial assessment yielded 75% agreement among the three coders, indicating a need for calibration before proceeding with full coding. Any coding discrepancies were then discussed among the coders to clarify definitions, refine theme boundaries, and ensure collective understanding (Creswell & Poth, 2016). This iterative process of discussion and refinement was repeated twice until inter-coder agreement reached 80% agreement, indicating a reliable framework. This refined and agreed-upon coding framework subsequently guided the final analysis of the entire dataset, which was conducted by the primary researcher.

Cultivating Reflexivity

Acknowledging that researcher perspectives influence qualitative interpretation is paramount (Berger, 2015). We engaged in ongoing reflexive practices for transparency and critical self-awareness. The three coders possessed diverse and complementary expertise, including proficiency in digital transformation, digital business, human-computer interaction, user judgment and decision-making, new product development, innovation management, sustainability, marketing research, blockchain, sustainability science, and the qualitative research methodologies (systematic review and reflexive thematic analysis) applied herein. Regular meetings facilitated discussions on how individual backgrounds and theoretical leanings might shape interpretations and theme development (Braun & Clarke, 2021), mitigating potential biases. Furthermore, an audit trail enhanced dependability and transparency (Lincoln & Guba, 1985), which included records of the search strategy, article selection, coding framework evolution, reflexive memos, and team discussions, ensuring a traceable research process. Throughout data extraction and analysis, researchers also engaged in systematic memoing (Saldaña, 2021). These reflections on the coding process, emerging patterns, and analytical challenges served as a tool for self-correction and tracking theme development (Birks et al., 2008).

Ensuring Validity through Theoretical Triangulation

To enhance analytical depth and bolster interpretation validity, we employed theoretical triangulation, systematically interpreting emergent themes through the lenses of DCT, RBV/NRBV, and Institutional Theory (as detailed in Section 3.4) (Denzin, 1978; Patton, 2015). This process involved a systematic mapping where emergent themes were methodically evaluated for resonance with the core constructs of such theories. Instances where a theme could be illuminated by multiple theories were explicitly documented and discussed by the research team. For instance, the theme "Sustainable Data Analytics and AI" simultaneously captured (i) organizational reconfiguration in line with DCT, (ii) a valuable and hard-to-imitate capability per RBV/NRBV, and (iii) a strategic response to coercive and normative pressures highlighted by Institutional Theory. These theoretical intersections were viewed as opportunities for a richer understanding of the organizational enablers for sustainable data practices (Flick, 2004). This approach ensured that interpretations were not confined to a single theoretical viewpoint, thereby contributing to a more robust conceptualization of our findings.

In applying the RBV, we used the VRIO framework [50]—Value, Rarity, Inimitability, and Organization—instead of the older VRIN model (Barney, 1991). This change reflects how RBV thinking has evolved, with "Organization" replacing "Non-substitutability" to better capture a firm's ability to support and apply its valuable resources. We found VRIO to be more suitable for our analysis, as it helps explain how organizations build and manage data capabilities for sustainability. It also fits well with our focus on Sustainable-by-Design Digital Transformation, where internal structures play a key role in turning data into a long-term strategic advantage.

Findings and Theoretical Synthesis

Core Themes of Sustainable Data Practices

From coded excerpts, we distilled seven themes that capture how organizations embed sustainability in data-driven DT. Each theme's prevalence, exemplar excerpt, and dominant theoretical lens (DCT, RBV/NRBV, or Institutional Theory) are detailed in the subsections that follow.

Sustainable Data Analytics & AI

This refers to the systematic application of advanced analytics, machine learning, and AI techniques to incorporate environmental and social criteria directly into data-driven decision processes. Rather than treating sustainability as an ex-post-performance indicator, organizations in this theme operationalize it within predictive models, optimization engines, and real-time dashboards so that ecological impact becomes an endogenous design variable in DT initiatives. The theme is highly salient in the review corpus, accounting for 246 of the 712 coded segments (34.6%) and appearing in 53 of 55 studies (96.4%). Line-level coding reveals a dual theoretical anchoring: most excerpts invoke a resource logic (RBV; 97 occurrences) by positioning proprietary analytics pipelines, sustainability data lakes, or context-specific AI models as valuable, rare, and difficult-to-imitate assets. A substantial minority frame the same practices through a DCT lens (64 occurrences), emphasizing the routines required to sense shifting ESG priorities, seize eco-efficient opportunities, and reconfigure data architectures over time. Institutional explanations (85 occurrences) are present but less dominant than the RBV logic, suggesting that firms adopt sustainable analytics primarily for strategic asset building and capability development rather than solely to satisfy coercive regulation.

A representative passage illustrates the interplay of both logics: "Integration of data from CAD, ERP, and MES enables real-time eco-impact dashboards for decision support." Here, semantic data integration is cast simultaneously as a scarce analytical resource that underpins competitive advantage (RBV) and as a reconfigurable sensing mechanism that allows continuous alignment with environmental targets (DCT). Collectively, the studies depict Sustainable Data Analytics & AI as a hybrid enabler: it is owned and protected like a strategic asset, yet it remains fluid, continually updated through learning loops and talent development to keep pace with technological advances and evolving stakeholder expectations. This dual character positions the theme as both a driver and an outcome of sustainable DT initiatives.

Strategic Digital-Transformation Alignment

Strategic DT Alignment captures the organizational mechanisms that keep DT goals explicitly tethered to enterprise-level sustainability strategies and key-performance indicators (KPIs). Typical practices include embedding ESG metrics into DT roadmaps, incorporating sustainability checkpoints in agile backlogs, and cascading planetary-boundary targets into data-platform OKRs. The theme is strongly represented in the corpus, accounting for 154 coded segments (21.6% of 712) and appearing in 40 of 55 reviewed papers (72.7%). Coding reveals that authors overwhelmingly invoke a dynamic-capabilities logic (DCT; 36 occurrences), emphasizing sensing of stakeholder expectations, seizing of eco-efficient opportunities, and continual reconfiguration of digital portfolios to maintain strategic fit. A minority of excerpts situate alignment efforts within an institutional frame, portraying them as responses to regulatory or normative pressures; RBV-style resource arguments are virtually absent, indicating that firms view alignment primarily as an adaptive routine rather than a scarce asset.

An illustrative passage states: "Digital transformation has been reframed as a pathway to corporate sustainability through stakeholder mapping and capability roadmaps." Here, stakeholder mapping functions as a sensing mechanism, while capability roadmaps guide the seizing and reconfiguring phases—hallmarks of DCT. Cross-paper comparison shows that alignment activities often start with top-down vision setting (e.g., net-zero strategy), followed by iterative recalibration of data platforms, analytics pipelines, and talent programs to ensure that digital initiatives continually advance declared sustainability outcomes. Overall, this theme emerges as the connective tissue between high-level sustainability ambition and day-to-day digital execution. Its dominance in DCT terms suggests that future research should probe how alignment routines evolve under conditions of technological turbulence and tightening ESG regulation, and whether institutional forces will play a more prominent role as disclosure standards mature.

Digital Capability Building & Learning

This encompasses internal initiatives—ranging from up-skilling programs and cross-functional design sprints to agile retrospectives and knowledge-sharing platforms—that cultivate enduring organizational capacity for responsible data practice. By embedding sustainability competencies into day-to-day routines, firms seek not only to comply with external demands but also to institutionalize continuous learning cycles that keep data governance, analytics methods, and cultural norms aligned with evolving environmental and social goals. The theme represents 103 coded segments (14.5% of the corpus) and is discussed in 38 of 55 studies (69.1%). Coding intensity is dominated by a dynamic-capabilities perspective (DCT; 33 occurrences), highlighting recurrent patterns of sensing skill gaps, seizing training opportunities, and reconfiguring workflows to integrate new sustainability know-how. Only isolated excerpts adopt an RBV or Institutional lens, signaling that scholars view capability building primarily as an adaptive routine rather than a scarce resource or a compliance response.

A representative excerpt notes: *"Cross-functional design sprints foster continuous learning and reuse of sustainability knowledge across projects."* Here, sprint-based experimentation reinforces both exploration (sensing new eco-data techniques) and exploitation (seizing and routinising them), hallmarks of the DCT cycle. Comparative analysis reveals three dominant sub-patterns: (i) structured training in ethical AI and green analytics, (ii) communities of practice that disseminate lessons learned from pilot projects, and (iii) iterative process audits that recalibrate data pipelines against emerging ESG benchmarks. Collectively, this theme functions as the human-centered counterpart to technology-centric themes: it equips personnel to operationalize sustainable data principles and ensures that such practices remain resilient amid technological churn and tightening stakeholder expectations. Future research should examine how these learning routines scale beyond early adopters and how they interact with institutional pressures as sustainability disclosure standards continue to evolve.

Circular Data Resource Management

This denotes lifecycle-oriented approaches that minimize data "waste," energy intensity, and hardware obsolescence by applying circular-economy principles—reduce, reuse, recycle—to the generation, storage, sharing, and eventual retirement of organizational data assets. Typical practices include de-duplication rules, data-retention tiers based on carbon intensity, and closed-loop protocols for repurposing archival datasets or re-deploying decommissioned storage hardware. The theme appears in 70 coded segments (9.8% of 712) and is covered by 33 of 55 studies (60.0%). Excerpts are overwhelmingly interpreted through a dynamic-capabilities lens (DCT; 69 occurrences), portraying circular practices as routines for sensing redundancy, seizing eco-efficient storage options, and continuously reconfiguring data architectures to align with sustainability objectives. Only a single instance invokes an RBV argument, and none rely primarily on institutional theory, indicating that scholars view circularity mainly as an internal capability rather than a strategic asset or compliance response.

An illustrative statement: *"Expandable mapping of product data characteristics to lifecycle processes reduces duplication and long-term storage overhead."* This passage exemplifies the reconfiguring phase of DCT: data schemas are iteratively redesigned to eliminate waste and support downstream reuse. Cross-study synthesis reveals three recurrent sub-mechanisms: (i) automated de-duplication and archiving policies tied to carbon budgets, (ii) metadata standards that facilitate dataset repurposing across projects, and (iii) hardware take-back or virtualization strategies that extend server lifespans while shrinking e-waste. Collectively, this theme positions sustainability not as an after-the-fact offset but as an endogenous design principle for data lifecycle governance. Its strong DCT grounding underscores the importance of organizational agility and learning in achieving circular outcomes; future work might explore whether, as carbon-accounting regulations tighten, institutional pressures will elevate compliance-driven motives alongside the current capability-driven narrative.

Data Integration & Interoperability

This comprises the standards, ontologies, and middleware that ensure semantic consistency and traceability across heterogeneous systems—design, production, supply-chain, and sustainability-reporting platforms—thereby enabling a unified, lifecycle view of organizational data. By breaking down silos, these mechanisms make environmental and social information available "at source," permitting downstream analytics, audit, and optimization without redundant data replication. The theme is evident in 54 coded of 712 segments (7.5 %) and addressed by 30 of 55 studies (54.5 %). Virtually all excerpts are interpreted through a dynamic-capabilities frame (DCT; 53 occurrences), highlighting integration work as an ongoing routine of sensing data-quality gaps, seizing interoperable standards, and reconfiguring schemas or APIs as business models evolve. Only one excerpt invokes institutional pressures, and none frame interoperability primarily as a rare resource, underscoring a capability-dominant narrative.

A representative excerpt states: *"A lifecycle design schema semantically connects design characteristics with downstream impact data."* This illustrates the reconfiguring phase of DCT, where schemas are continuously refined to propagate sustainability attributes through the data value chain. Thematic synthesis identifies three recurring sub-practices: (i) adoption of open ontologies (e.g., ISO 14040 life-cycle indicators) for semantic alignment, (ii) API gateways that inject ESG fields into enterprise data buses, and (iii) blockchain or provenance tags that preserve traceability without duplicating datasets. Overall, this theme emerges as the connective infrastructure that underpins other themes—analytics, circularity, governance—by guaranteeing that sustainability metadata remain intact from source to report. Its heavy reliance on DCT signifies that successful integration is less about possessing unique assets and more about orchestrating agile, cross-system reconfiguration. Future research should investigate how emerging interoperability mandates (e.g., EU Data Act) may introduce stronger institutional drivers into what is currently a predominantly capability-focused arena.

Energy-Efficiency & Real-Time Optimization

This theme captures the use of sensor networks, edge analytics, and feedback-control algorithms to reduce energy consumption, carbon emissions, and material waste in operational processes. By streaming high-granularity data, organizations can detect inefficiencies instantaneously and enact automated set-point or scheduling adjustments that embed sustainability into day-to-day operations. The theme comprises 53 coded of 712 segments (7.4%) and is represented in 30 of 55 articles (49.1%). Excerpts are still led by a dynamic-capabilities interpretation (DCT; 23 occurrences), underscoring the routines of sensing (real-time monitoring), seizing (deploying optimization algorithms), and reconfiguring (continually calibrating devices and control logic). Almost as many passages frame the same practices as valuable resources (RBV; 22 occurrences), while Institutional explanations appear in 8 excerpts, typically invoking energy-efficiency standards or carbon-pricing schemes.

An exemplar statement notes: "…monitor their environmental impact, optimize resource usage, and enhance supply-chain transparency." This sentence illustrates a sensing–seizing loop: real-time monitoring identifies inefficiencies, and optimization routines seize the opportunity by reallocating resources. Cross-paper synthesis reveals three dominant sub-patterns: (i) edge AI that minimizes sensor-to-cloud traffic, lowering both latency and power draw; (ii) predictive maintenance that reduces downtime and unnecessary part replacements; and (iii) demand-response scheduling that shifts energy-intensive tasks to low-carbon time windows. Collectively, this theme operationalizes sustainability "in flight," turning continuous data streams into immediate emissions savings. Its pronounced DCT orientation—supplemented by RBV arguments—suggests that value lies less in possessing unique sensors and more in orchestrating rapid learning cycles that translate data into eco-efficient action. Future research should explore how forthcoming net-zero regulations may elevate institutional drivers and whether firms can formalize these optimization routines into VRIN-type analytics assets over time.

Governance & ESG Reporting

This encompasses the policies, organizational structures, and data-assurance mechanisms that ensure ethical handling of data and provide transparent disclosure of ESG performance. Typical practices include assigning data-steward roles, instituting cross-functional ESG committees, automating evidence collection for sustainability audits, and embedding assurance rules within data pipelines to guarantee traceable, verifiable metrics. Although less frequent than the preceding themes, Governance & ESG Reporting still registers 32 coded of 712 segments (4.5%) and features in 10 of 55 studies (18.2 %). Coding shows a strong institutional orientation (Institutional Theory; 19 occurrences): many authors portray governance routines as responses to coercive or normative pressures, such as evolving disclosure mandates and industry standards. DCT explanations appear in 7 occurrences, emphasizing sensing of regulatory shifts, seizing of digital tools for automated disclosure, and reconfiguring of policies to keep pace with new requirements; RBV arguments are evident in 6 occurrences, framing trusted reporting infrastructures as valuable organizational assets.

A representative quotation demonstrates this capability emphasis: *"This study proposes the adoption of natural-language processing to identify and auto-populate the consolidated ESG matrix."* Here, automated extraction and population of ESG indicators illustrate a seizing–reconfiguring loop that continually updates disclosure content. Thematic synthesis reveals three main sub-mechanisms: (i) machine-readable policy engines that enforce data-ethics rules at source, (ii) blockchain-backed provenance tags to verify reported figures, and (iii) role-based dashboards that integrate financial and non-financial indicators for board oversight. Overall, this theme functions as the institutional backbone that legitimizes data-centric sustainability claims, even though current scholarship frames it more as an adaptive capability than a compliance reflex. Future research should examine whether impending mandatory ESG-data-quality regulations shift the discourse toward an institutional logic, and how organizations might leverage RBV considerations—e.g., trusted reporting infrastructures—as sources of competitive differentiation.

Theory Utilization Patterns

Figure 3 depicts the prevalence of the three principal lenses—DCT, RBV/NRBV, and Institutional Theory—across the 55 studies in our review corpus, while Table IV cross-tabulates each lens with the seven core themes identified in the previous section. DCT and RBV/NRBV are invoked by every article, indicating that scholars habitually frame sustainable data practices simultaneously as capabilities to be reconfigured and resources conferring strategic advantage. Institutional Theory appears in 93 % of papers, a modest decline that suggests a minority of studies interpret sustainability primarily as an internally driven agenda rather than a response to external pressures.

In this descriptive analysis, the AI–related themes attract the broadest coverage—co-occurring with DCT in 54 papers, RBV/NRBV in 46, and Institutional Theory in 34—underscoring that algorithmic initiatives are viewed as capability building, resource investment, and compliance risk in near equal measure. By contrast, *Digital Capability Building* is theorized predominantly through DCT (41 papers) and RBV/NRBV (33), with far fewer references to Institutional logics (17), implying that authors conceptualize internal reconfiguration as the primary explanatory mechanism. A similar inward bias characterizes *Circular Data Resource Management*, where DCT dominates (36 papers) and institutional pressures are rarely foregrounded (10 papers).

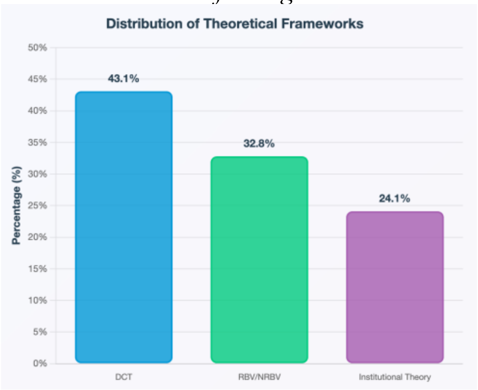

Figure 3 Theory Utilization Across Collected Articles

Themes	DCT	RBV/NRBV	INSTITUTIONAL THEORY
Sustainable Data Analytics & AI	57	51	35
Strategic DT Alignment	43	32	27
Governance	13	8	12
Circular Data Resource Management	36	24	10
Digital Capability Building	41	33	17
Data Integration	32	16	19
ESG Reporting	13	8	12

Table 4: Frequency of DCT, RBV/NRBV, and Institutional Theory Utilization across the Seven Core Themes

This review yields three clear implications. First, because scholars almost always discuss DCT together with the RBV/NRBV, the two lenses risk becoming conceptually redundant. Future studies should spell out when sustainability initiatives centered on data are better understood as *capabilities* and when they are better understood as *resources*, or else examine empirically how the two perspectives complement one another. Second, Institutional Theory appears far less often in the literature, leaving a gap in our understanding of how coercive, normative, and mimetic pressures influence the adoption of responsible data practices—especially in highly regulated areas such as ESG disclosure and circular-economy requirements. Third, governance-focused topics, for example, ESG reporting and circular data management, rarely draw on RBV/NRBV. This is a missed opportunity to frame disclosure routines and stewardship practices as organizational assets that are valuable, scarce, and difficult for competitors to replicate. Overall, the evidence portrays a theoretically rich yet fragmented landscape. Advancing the field will require integrative, multi-lens designs—such as configurational or mixed-methods studies—that can explicate how capability, resource, and institutional logics interact to underpin sustainable digital-transformation outcomes.

An Integrated Framework for Organizational Enablers

This section presents an integrated framework (depicted in Figure 4) that synthesizes multilevel organizational and external drivers, interpreted through three theoretical lenses to explain how sustainability can be embedded into data practices. Recognizing data as a core digital resource within the DT journey, the framework addresses a critical gap in current literature: the absence of structured guidance on how organizations can proactively operationalize sustainability across the data lifecycle. Grounded in Perspective A, this model views sustainability not as a downstream outcome, but as a foundational design principle that must be internalized through the processes, structures, and governance of data-driven transformation initiatives. The development of the framework also employed a reflexive qualitative approach. It involved iterative interpretation and sensemaking by the research team the same way we have already interpreted in Section 4. Emergent themes were mapped to relevant theoretical constructs, and overlapping theoretical interpretations were retained to reflect the complexity of organizational contexts.

Framework Composition

The framework is structured around three layers that collectively explain how organizations can embed sustainability into their data practices. Together, they provide a multilevel perspective that captures both the conditions that enable change and the outcomes that define sustainable transformation. The detailed literature mapping, explaining how the following elements with detailed description are analyzed is evident in Appendix A.

External and Organizational Drivers identify the key forces that shape an organization's intent and readiness for sustainable transformation. External drivers include regulatory pressures, stakeholder expectations, ecosystem collaborations, and technology trends. Organizational drivers refer to internal enablers, such as data governance, infrastructure, culture, and digital capabilities, which determine how effectively external pressures are translated into action. These elements serve as foundational preconditions for initiating sustainability-oriented change.

A Transformation Maturity Model that captures the progression of data practices across three stages: Foundational, Integrated, and Transformative. These stages are interpreted through 3 + 1 theoretical lenses. DCT explains how organizations build capabilities through sensing, seizing, and reconfiguring. Institutional Theory illuminates the role of external legitimacy and conformity. RBV focuses on the strategic value of data capabilities as valuable, rare, inimitable, and organizationally embedded assets, while NRBV adds a sustainability lens through concepts such as pollution prevention and clean technology.

Sustainability Targets represent strategic outcomes that operationalize ESG principles within data systems and processes. These targets act as design principles that organizations should strive toward as they mature in their transformation journey. Each layer reinforces the others, ensuring vertical coherence between enabling conditions, developmental pathways, and sustainability outcomes.

Drivers and Enablers of Sustainable Data Transformation

This section outlines the key drivers that shape an organization's capacity to embed sustainability into its data practices during the DT journey. These drivers are classified into two categories: external and organizational. While external drivers represent contextual pressures and opportunities that stimulate transformation, organizational drivers reflect internal capabilities that determine how effectively sustainability principles are absorbed and operationalized.

External Drivers

Four external drivers underpin the environmental conditions that prompt organizations to evolve their data practices. Based on our synthesis, first, *Inter-Organizational Data Ecosystems* highlight the influence of platform-based collaborations and industry alliances, where shared data infrastructure fosters circularity and interoperability (DCT – sensing; Institutional – normative). *Regulatory and Policy Pressures* compel organizations to align data governance and ESG disclosures with evolving legal standards and global sustainability mandates (Institutional – coercive; RBV – compliance as capability). *Stakeholder and Societal Expectations* exert normative pressures that encourage transparency and responsiveness in sustainability data, reinforcing legitimacy through external accountability (Institutional – normative; RBV – reputation asset). Finally, *Technological Advancements and Innovation Pressure* reflect the accelerating pace of digital innovation—particularly in AI, big data, and IoT—which acts as both an enabler and a disruptor, challenging firms to continuously adapt their data systems and extract value from emerging tools (DCT – sensing/seizing; RBV – strategic digital resources).

Organizational Drivers

Six organizational enablers that serve as the internal foundation are synthesized. First, a *Data-Driven Organizational Culture* fosters a shared mindset that positions data, including ESG metrics, as central to decision-making and innovation (DCT – sensing/seizing; RBV – cultural asset; Institutional – normative). *Data Governance and Quality Management* provides formal structures to ensure data accuracy, ethics, and compliance, thus enabling trustworthy sustainability analytics and reporting (RBV – valuable routines; Institutional – coercive/normative). *Advanced Data Analytics Capabilities* empower organizations to extract insights from complex datasets to drive green decision-making and optimize resource use (DCT – sensing/seizing; RBV/NRBV – analytics capital). *Integrated Data Infrastructure* supports the seamless flow of sustainability-related data across business units, enabling interoperability and reducing inefficiencies (DCT – reconfiguring; RBV – scalable IT asset). *Data Transparency and Performance Reporting* ensures visibility of sustainability metrics both internally and externally, reinforcing accountability and continual improvement (Institutional – normative/coercive; DCT – learning; RBV – reputation). Lastly, *Employee Data Literacy and Training* enhances human capital by equipping employees with the skills to interpret, act on, and innovate with sustainability data (DCT – transforming; RBV – human capital).

Collectively, these enablers form a coherent organizational response system that translates external sustainability drivers into internalized routines and innovations. They not only support compliance and alignment but also foster strategic foresight, adaptability, and ESG-driven value creation in the context of sustainable data transformation.

Maturity Paths and Theoretical Integration

To explain how organizations embed sustainability into their data practices, the framework introduces a three-stage maturity model: Foundational, Integrated, and Transformative. Each level reflects increasing capability, intentionality, and sustainability alignment in the use and governance of data. These stages are interpreted through the combined lenses of DCT, RBV/NRBV, and Institutional Theory. Together, they illuminate not only what capabilities emerge but how and why organizations adapt them within different institutional and environmental contexts.

Our three-stage maturity model offers a clear and logical framework for organizations to embed sustainability into their data practices. This staged approach is well-supported by established theories of organizational capability development and digital maturity. The progression begins with the *Foundational* stage, where essential, often siloed, capabilities are established, mirroring the initial phases of process maturity (Mettler & Pinto, 2018; Paulk et al., 1993). As an organization advances, it enters the *Integrated* stage by embedding these sustainable data practices within core business processes and governance structures. Finally, the *Transformative* stage is achieved when these capabilities are leveraged to drive strategic innovation and create sustainable business models, reflecting a state of digital mastery where technology becomes a core driver of business transformation (Westerman et al., 2014). This streamlined three-phase progression provides an accessible and actionable roadmap for organizations to develop and leverage their sustainable data capabilities.

DCT for Sustainable Data Maturity

From the DCT perspective, maturity unfolds through the development of three interrelated capabilities: sensing, seizing, and reconfiguring. At the Foundational level, sensing is limited to basic internal data monitoring, and seizing is ad hoc relying on periodic reporting with minimal strategic foresight. Reconfiguring is constrained by rigid, siloed data systems and legacy infrastructure. As firms progress to the Integrated stage, sensing expands to include diverse internal and external ESG data sources; seizing becomes data-informed, as analytics guide opportunity evaluation and decision-making; and reconfiguring emerges through the adoption of adaptive IT, cross-functional workflows, and sustainability-aware system redesign. At the Transformative level, firms display intelligent sensing through real-time, AI-powered analytics; they seize opportunities dynamically using predictive insights embedded with sustainability criteria; and they achieve continuous reconfigurability through modular, cloud-native, and circular-ready architectures. Sustainability-by-design becomes fully institutionalized in every adaptation.

RBV/NRBV for Sustainable Data Maturity

RBV offers a lens to evaluate how data capabilities evolve into strategic assets as organizations advance in DT maturity. According to the VRIO framework—Value, Rarity, Inimitability, and Organized to Exploit—data resources mature from fragmented and underutilized toward becoming durable sources of competitive advantage. At the Foundational stage, value is incidental. Basic ICT infrastructure supports data collection for operational needs, but ESG integration remains ad hoc. Pockets of sustainability data exist, yet they are rarely analyzed for strategic insight. Rarity and inimitability are low—organizations may start building isolated life-cycle data maps, but semantic schemas and analytic capabilities are immature. Exploitation of data is minimal, as sustainability-related repositories are siloed and poorly governed. At the Integrated stage, value becomes more systematically captured. Standardized interfaces for ESG and life-cycle data enable routine use in performance monitoring and reporting. Rarity increases as firms develop proprietary sustainability metrics, often embedded in Green-ICT governance. These assets are difficult to source externally. Inimitability grows as organizations implement end-to-end data integration (e.g., CAD-ERP-MES) that embeds sustainability into workflows. Organizational exploitation becomes more intentional, with role-based access, trustworthy controls, and linked data structures that support cross-functional decision-making. At the Transformative stage, data ecosystems are regenerative, and sustainability-by-design is fully operational. Value is continuously generated through systems such as digital product passports, which track provenance and offer instructions for repair, recycling, and reuse. AI-driven pipelines extract rare insights from multi-source ESG data, creating a competitive advantage that is both technical and environmental. Inimitability is fortified by automated feature extraction and domain-specific tacit knowledge embedded in workflows. Finally, data is systematically exploited across the enterprise and partner networks via embedded LCA knowledge and semantically rich platforms that support circular innovation.

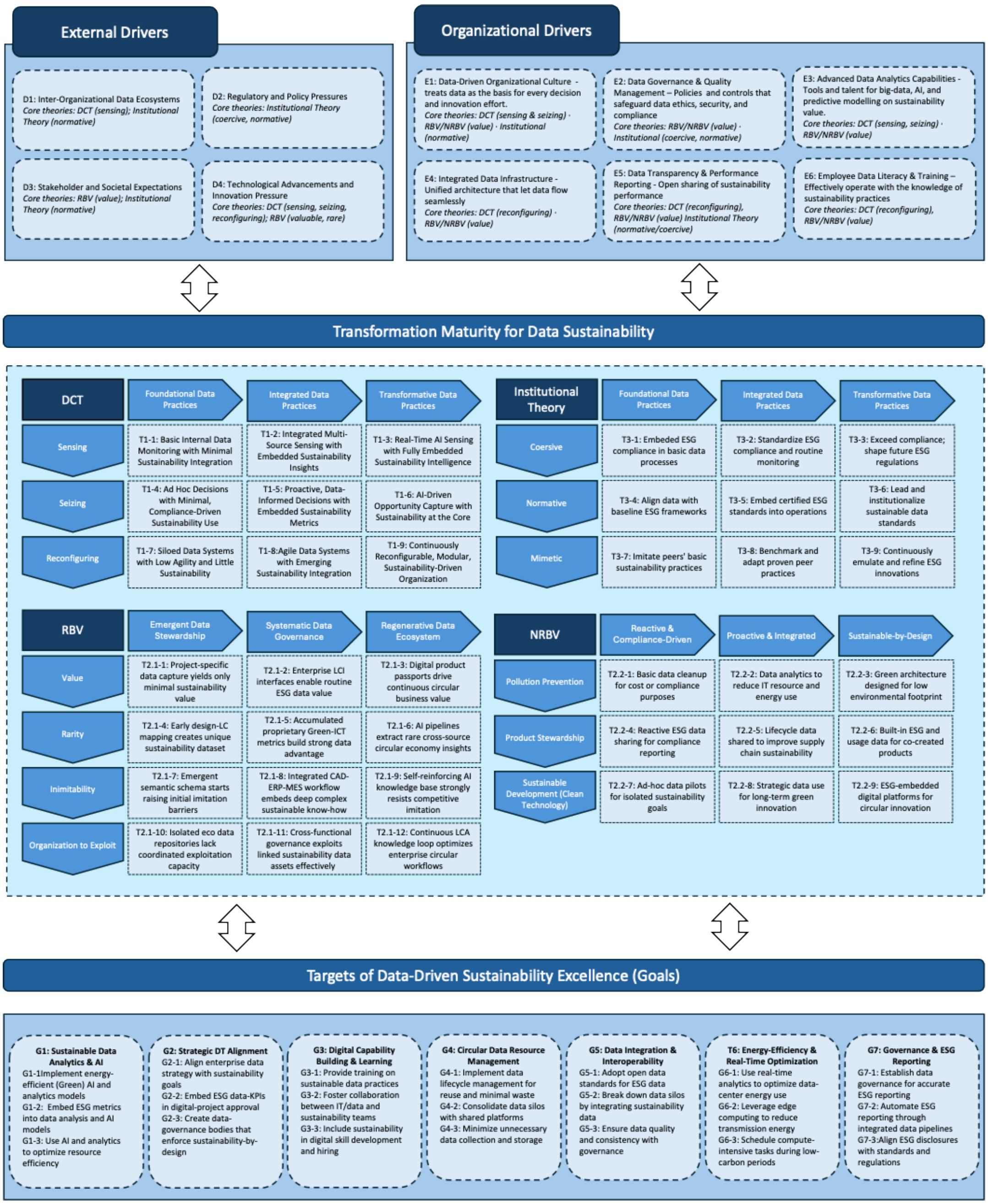

Figure 4 An Integrated Framework for Embedding Sustainability into Data Practices

Complementing RBV, NRBV adds a sustainability-centric perspective by classifying maturity into three trajectories, each evolving from reactive to sustainable-by-design. For Pollution Prevention, foundational organizations adopt basic digital efficiency measures (e.g., server optimization) primarily for cost or compliance reasons. As maturity increases, proactive analytics are used to minimize resource consumption and energy use. At the transformative level, data systems are designed upfront for low environmental impact, incorporating green algorithms and renewable-powered infrastructure as default system criteria. In Product Stewardship, foundational practices involve disclosing minimal ESG metrics to comply with regulations or market pressure. At the intermediate level, lifecycle data is systematically collected and shared across the supply chain to inform sustainability improvements. Transformative firms integrate stakeholder input and ESG data from the outset of product or service development, enabling co-created offerings built on circular economy principles and real-time impact tracking. For Sustainable Development, immature firms launch isolated data-driven sustainability projects—typically philanthropic or compliance-driven. With maturity, data strategies begin aligning with long-term ESG goals, using IoT and big data to identify sustainable business opportunities. At the highest level, sustainability becomes an intrinsic design outcome of digital innovation. New AI platforms, digital services, and governance models are built explicitly to deliver environmental and social value—thus positioning the organization as a sustainability leader.

Together, the RBV/ NRBV lenses explain how data transitions from a passive asset to a sustainability-enabling capability that is economically valuable, strategically rare, and organizationally embedded—paving the way for transformative, sustainable digital transformation.

Institutional Theory for Sustainable Data Maturity

Institutional Theory offers a lens to understand how ESG data practices evolve in response to external pressures. At the Foundational level, organizations adopt basic ESG data governance to meet regulatory mandates (coercive), follow emerging industry standards in a minimal form (normative), and imitate simple peer practices, such as dashboards or compliance reports (mimetic). These efforts are largely reactive, and compliance driven. At the Integrated stage, data governance becomes more structured and professionalized. Regulatory requirements are systematically embedded into processes, enabling routine monitoring of ESG metrics (coercive). Organizations also incorporate recognized standards and certifications, making sustainable data management a part of professional practice (normative). Benchmarking becomes proactive, with firms adopting best practices and tools from leading peers (mimetic). At the Transformative stage, organizations move beyond compliance to shape institutional expectations. They not only exceed regulatory standards but also contribute to shaping future ESG policies through leadership in data governance (coercive). Sustainable data practices are fully institutionalized, with firms playing a role in setting industry norms and frameworks (normative). These organizations become benchmarks themselves, continuously refining cutting-edge practices and influencing others in their ecosystem (mimetic). Here, ESG data governance becomes a source of strategic legitimacy and institutional leadership.

These theoretical lenses intersect in key capabilities. For instance, the theme of “Sustainable Data Analytics and AI” illustrates how transformative maturity simultaneously activates DCT (through continuous sensing and adaptive reconfiguration), RBV/NRBV (by building unique, hard-to-copy analytic capabilities that generate environmental value), and Institutional Theory (by embedding industry norms and responding to stakeholder demands for transparent, AI-enabled ESG reporting). Altogether, this integrative model helps explain not just whether a firm is progressing in its digital sustainability journey, but how and why such progression occurs. It reveals that maturity is not merely technical—it is strategic, institutional, and intentional. As such, the framework offers a dynamic and multi-dimensional roadmap for how data, when governed and used appropriately, becomes a vehicle for embedding sustainability into the heart of digital transformation.

Targets of Data-Driven Sustainability Excellence

The final layer identifies seven strategic sustainability target areas that align ESG imperatives with data practices associated with our core themes of sustainable data practices in Section 4.1. These targets serve as design principles that translate DT maturity into measurable sustainability outcomes across technical, governance, and human resource dimensions.

Sustainable Data Analytics & AI emphasizes three core objectives: implementing energy-efficient AI and analytics models, embedding ESG metrics into analytical processes, and using AI to optimize resource efficiency. These practices reduce the carbon footprint of data-related operations while integrating sustainability criteria into data modelling, analysis, and decision-making. *Strategic Digital-Transformation Alignment* includes aligning enterprise data strategies with sustainability goals, embedding ESG data KPIs into digital project evaluations, and establishing governance bodies (e.g., Green Data Steering Committees) that oversee sustainability-by-design principles in data architecture and decision-making. *Digital Capability Building & Learning* focuses on developing internal capacity for sustainable data practices. It involves providing training on green data management and ethical AI, fostering collaboration between IT and sustainability teams, and incorporating ESG-related knowledge into digital skill development and hiring processes. *Circular Data Resource Management* targets minimizing data waste and enabling reuse through data lifecycle management, consolidation of silos via shared platforms, and data minimization practices that reduce unnecessary collection and storage. *Data Integration & Interoperability* addresses technical infrastructure by promoting the adoption of open data standards and APIs, integration of sustainability data across disparate systems, and data quality measures that ensure reliability and consistency for ESG applications. *Energy-Efficiency and Real-Time Optimization* includes using real-time analytics to optimize data center energy use, leveraging edge computing to reduce transmission loads, and scheduling compute-intensive tasks during low-carbon periods. Finally, *Governance and ESG Reporting* supports accurate and transparent disclosures by establishing robust data governance, automating ESG reporting pipelines, and aligning data practices with recognized reporting frameworks and regulatory expectations.

Future Research Directions

This section synthesizes research gaps and future directions using our proposed framework. We analyze the extent to which current work aligns with three theoretical lenses—DCT, RBV/NRBV, and Institutional Theory. This analysis highlights key areas of emphasis, underexplored themes, and emerging opportunities to guide future research in sustainable data transformation. The reference codes (e.g., T1-1, T2-9) correspond to those shown in Figure 4.

Future Directions through the Lens of DCT Framework

Synthesizing the current literature through the lens of DCT reveals a clear trajectory for advancing sustainable data transformation, with future research clustered around the core capabilities of sensing, seizing, and reconfiguring. Within the *sensing* dimension, scholars call for the development of semantic representations that capture lifecycle impacts in digital product design, enabling AI to detect sustainability-relevant signals in real time (T1-3) (Tschiltschke et al., 2024). Participatory approaches and digital product passports are further recommended to enhance multi-source sensing and reduce information asymmetries along value chains (T1-2)

(Klusch & Hielscher, 2025). In the *seizing* domain, future work emphasizes the need to examine stakeholder roles and psychosocial dynamics in sustainability-driven digital transformation, paving the way for more informed and proactive decision-making underpinned by embedded sustainability metrics (T1-5) (Nishant et al., 2020). AI-enabled opportunity capture, particularly for circular economy integration among MSMEs, also emerges as a strategic priority (T1-6) (Martínez-Peláez et al., 2023). Finally, in the *reconfiguring* dimension, researchers advocate for exploring coherent policy frameworks and institutional support mechanisms that facilitate the transformation of legacy infrastructures into agile, modular, and sustainability-oriented systems (T1-8, T1-9) (Del Río Castro et al., 2021). Across these domains, a consistent theme emerges: the need to move beyond compliance-driven routines toward embedding sustainability as a design principle at the core of digital transformation. This reinforces the salience of Perspective A, where sustainability is not an afterthought but a foundational element shaping the next generation of resilient and responsible digital systems.

RBV/NRBV

Viewed through the complementary lenses of the RBV and the NRBV, future research emphasizes the strategic elevation of data practices to drive both organizational advantage and environmental sustainability. From the RBV perspective, data assets are increasingly seen as critical to enhancing value, rarity, inimitability, and the capacity for effective exploitation. Studies underscore the role of semantic representations and lifecycle impact modeling in shifting from isolated value capture (T2.1-1) toward enterprise-level ESG optimization (Tschiltschke et al., 2024), while digital product passports are positioned as enablers of continuous circular value through enhanced transparency (T2.1-3) (Klusch & Hielscher, 2025). The development of unique sustainability datasets through early design-lifecycle mapping and stakeholder engagement provides rare, defensible insights (T2.1-4, T2.1-6) (Martínez-Peláez et al., 2023; Nishant et al., 2020), with AI further supporting cross-source knowledge extraction. To reinforce inimitability, scholars highlight the importance of emergent semantic schema and integrated digital workflows that embed sustainability knowledge at a deep, systemic level (T2.1-7, T2.1-8) (Tschiltschke et al., 2024). Organizational capacity is likewise strengthened through cross-functional governance and policy-aligned knowledge loops, facilitating a transition from fragmented repositories to regenerative, learning-based data ecosystems (T2.1-10, T2.1-12) (Del Río Castro et al., 2021). Concurrently, the NRBV directs attention to the environmental implications of digital systems, promoting pollution prevention through green architectural design and energy-efficient analytics (T2.2-2, T2.2-3) (Martínez-Peláez et al., 2023; Tschiltschke et al., 2024). Product stewardship is evolving through deeper ESG integration and participatory data frameworks that enhance supply chain transparency and consumer empowerment (T2.2-4, T2.2-6) (Klusch & Hielscher, 2025), while sustainable development goals are advanced through ESG-embedded platforms and AI-supported innovation that reflect long-term environmental commitments (T2.2-8, T2.2-9) (Del Río Castro et al., 2021; Nishant et al., 2020). Together, these research directions signal a maturing field that integrates strategic and ecological priorities, advancing toward data ecosystems that are not only competitively resilient but also environmentally regenerative by design.

Institutional Theory

Guided by Institutional Theory, future research on ESG-aligned data practices is increasingly shaped by the interplay of regulative, normative, and mimetic pressures, reflecting a shift from technical adoption toward institutional embedding. At the *regulative* level, scholars highlight the need to formalize ESG compliance through digital architectures and lifecycle modeling, advancing beyond routine monitoring toward more proactive roles in shaping regulatory frameworks (T3-2, T3-3) (Klusch & Hielscher, 2025; Martínez-Peláez et al., 2023; Tschiltschke et al., 2024). Meanwhile, the *normative* dimension draws attention to aligning data governance with certified ESG standards and embedding sustainability principles into organizational systems through stakeholder engagement and long-term institutionalization (T3-5, T3-6) (Nishant et al., 2020). This is reinforced by participatory frameworks that empower consumers and supply chain actors to co-define sustainable norms. On the *mimetic* front, the deployment of digital product passports and the diffusion of best practices—especially among MSMEs participating in global sustainability efforts—illustrate how organizations adapt by emulating peer benchmarks and evolving shared expectations (T3-9) (Del Río Castro et al., 2021). Together, these institutional forces underscore a broader transformation: from isolated ESG initiatives to a legitimized, standardized, and socially embedded foundation for sustainable data practices within digital transformation ecosystems.

Discussion and Theoretical Implications

We first revisit the research questions, synthesizing the findings from our systematic review and theoretical analysis to offer clear answers, highlight theoretical patterns, and expose remaining gaps in the literature.

RQ1: What organizational enablers embed sustainability principles into data-related DT initiatives? This review reveals a compelling narrative: sustainability is no longer a peripheral concern but is increasingly being hardwired into the very fabric of data-driven digital transformation. Across the literature, seven key organizational enablers emerge—ranging from strategic alignment and capability building to circular data governance and AI-driven sustainability analytics. These enablers are not isolated interventions but interdependent mechanisms that reshape how organizations think about, design, and manage their data ecosystems. Critically, they signal a shift from treating sustainability as an outcome to embedding it as an intentional design principle—what we term Sustainable-by-Design DT (Perspective A). Theoretically, this transformation is best captured through the lens of DCT, where sensing emerging ESG imperatives, seizing digital opportunities, and reconfiguring systems form the backbone of organizational adaptation. Complementing this, the RBV/NRBV explains how practices like sustainable analytics and ESG reporting become durable, inimitable assets. Institutional Theory, while less prominent, provides crucial insight into how regulatory, normative, and mimetic pressures accelerate this shift—particularly in domains like data governance and ESG assurance. Taken together, these findings fill a significant gap in the literature by offering an integrated, multilevel explanation of how sustainability can be operationalized within data-centric DT. For practitioners and scholars alike, the message is clear: embedding sustainability into the data lifecycle is not only possible—it is increasingly essential for legitimacy, resilience, and long-term advantage.

RQ2: How extensively do existing studies employ DCT, RBV/NRBV, and Institutional Theory when analyzing sustainable data practices? Our analysis reveals a theoretically rich but uneven landscape. Among the 55 studies reviewed, DCT and the RBV/NRBV are frequently employed, often in tandem, to explain how organizations build adaptive capacity and leverage data as a strategic asset for sustainability. DCT dominates, particularly in discussions of sensing ESG priorities, seizing digital opportunities, and reconfiguring systems—core to themes like strategic alignment, circular data practices, and capability development. RBV/NRBV complements this by positioning sustainability-enabling data capabilities—such as proprietary analytics models or green data pipelines—as valuable, rare, and inimitable. However, the overlap in usage suggests a potential theoretical redundancy that future research must disentangle: when are sustainable data practices better conceptualized as capabilities, and when as resources?

In contrast, Institutional Theory is notably underutilized—despite its strong explanatory power in understanding how external pressures shape data governance. Where it does appear, it clarifies how coercive regulation, normative standards, and mimetic benchmarking shape ESG reporting and ethical data practices. Yet it is rarely applied to explain internal transformation, capability building, or innovation processes—leaving a critical blind spot. By systematically mapping how these three theories intersect across the literature, this review offers not only a snapshot of current theoretical preferences but also a roadmap for more balanced and integrative theorizing. It urges future scholars to move beyond siloed application and instead explore how dynamic capabilities, strategic resources, and institutional legitimacy interact to drive sustainable digital transformation from within.

RQ3: Where do empirical and theoretical gaps remain in the literature? This review uncovers significant empirical and theoretical gaps, particularly from Perspective A embedding sustainability within data practices. Empirical research on data practices—distinct from infrastructure or digital tools—is still sparse and fragmented, limiting generalizability and ignoring contexts with high social impact. Theoretical applications are similarly imbalanced, with a strong emphasis on DCT and RBV/NRBV, while Institutional Theory remains underused. It is often limited to compliance-driven ESG reporting rather than examined as a driver of normative or regulatory transformation. The intersection between institutional pressures and the development of sustainability-related resources and capabilities is rarely explored. There is limited integration across these theoretical lenses—dynamic sensing and reconfiguring processes, for example, are seldom analyzed alongside institutional triggers like regulations, certifications, or stakeholder activism. This fragmentation contributes to conceptual redundancy and missed opportunities to understand how institutional forces influence strategic sustainability capabilities. Methodologically, most studies remain cross-sectional, conceptual, or descriptive, lacking longitudinal or causal designs necessary to trace how sustainable data practices evolve. As a result, the field offers little clarity on which organizational enablers truly matter and under what conditions. Addressing these limitations will require multi-theoretical, mixed-methods research that captures the interplay of strategy, capability, and legitimacy—charting a path forward for a more integrated and impactful research agenda.

Theoretical Contributions

This study advances the emerging literature on Perspective A—sustainable-by-design digital transformation—by positioning data practices, rather than infrastructure, as the primary locus through which sustainability is embedded. Prior research has largely emphasized green IT or energy efficiency, but this review reframes sustainability as a function of how data is governed, used, and transformed within organizations. Synthesizing findings from 55 studies and structured through a maturity framework informed by DCT, RBV/NRBV, and Institutional Theory, the study offers three key theoretical contributions. First, it operationalizes DCT at the level of data governance, revealing how *sensing*, *seizing*, and *reconfiguring* manifest in ESG analytics, circular data strategies, and semantic interoperability. Second, it extends RBV/NRBV by showing how data-driven sustainability becomes a source of strategic advantage—valuable, rare, and embedded—especially when aligned with stakeholder and regulatory expectations. Third, it bridges with institutional theory by demonstrating how regulatory pressures, such as ESG mandates, catalyze capability development beyond compliance toward normative transformation. Together, these insights reposition sustainable data transformation as a multidimensional process—driven not only by technology but by organizational routines, strategic assets, and evolving legitimacy demands.

Managerial Implications

This review translates theoretical insights into actionable guidance for managers seeking to embed sustainability into DT, specifically through data governance and lifecycle practices. We distil two practitioner-ready tools grounded in our synthesis (see Appendix): (1) *Action-oriented guideline* derived from seven core thematic enablers, and (2) *Three-phase maturity roadmap* that charts an organization's path from initial experimentation to sustainability-by-design. The action guideline transforms conceptual insights into practical directives, linking each theme to targeted actions, ESG-aligned KPIs, and capability investments. Our *maturity roadmap* presents a theory-informed model for organizational progression across three stages. In the *Foundational* phase, sustainability efforts are fragmented and compliance-driven, characterized by minimal sensing and immature governance. As firms evolve into the *Integrated* stage, sustainability principles become embedded in operations: ESG metrics are woven into data systems, standardized frameworks adopted, and cross-functional coordination ensures transparency. At the *Transformative* stage, sustainability is no longer an add-on but a foundational design logic. Organizations deploy AI for real-time ESG sensing, develop regenerative data ecosystems using digital product passports, proactively shape institutional norms, and build platforms explicitly designed for environmental value creation.

Together, these tools provide a coherent bridge between theory and practice. They offer a structured pathway for organizations to shift from isolated sustainability initiatives toward enterprise-wide, regenerative data transformation. By aligning internal capabilities, organizational culture, and institutional dynamics, firms are not only better positioned to meet regulatory and societal expectations—but also to unlock enduring strategic advantage through responsible, future-ready data governance.

Conclusion

This review provides a theory-informed and practice-oriented synthesis of how organizations can embed sustainability into their data practices throughout the digital transformation journey. By analyzing 55 studies through the lenses of Dynamic Capabilities Theory, Resource-Based and Natural Resource-Based Views, and Institutional Theory, we develop a structured maturity framework capturing organizational enablers, multilevel drivers, and ESG-aligned strategic outcomes. Unlike prior research that frames sustainability as a downstream result of DT, our model positions sustainability as a design principle embedded across the data practices. This contribution advances both academic understanding and managerial application by articulating how internal capabilities, external pressures, and strategic routines converge to shape sustainable-by-design data transformation.

While this review offers valuable insights, certain limitations must be acknowledged. First, the analysis is based on a purposive sample of 55 articles, which may limit generalizability across industries and regions. Second, the corpus is restricted to English-language publications, introducing potential language and cultural biases. Third, our theoretical coding relies on the authors stated frameworks and concepts, which may omit relevant but implicit mechanisms or constructs. These constraints underscore the need for continued empirical expansion and theoretical triangulation in future research.

To further validate and extend this framework, future research should embrace mixed-methods designs that combine qualitative depth with quantitative rigor. Cross-country comparisons would help reveal how institutional, cultural, and regulatory differences shape the embedding of sustainability within data practices. Longitudinal studies are especially needed to trace how capabilities evolve across maturity stages and how external pressures—such as ESG regulations or stakeholder activism—trigger strategic adaptations. Additionally, further work could explore the interplay of emerging technologies like generative AI and blockchain with sustainable data governance, offering new avenues for innovation that are both ethically aligned and ecologically conscious.

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Appendices

No.	Title
1	Digitally integrated sustainability assessment of design characteristics – A systematic review (Tschiltschke et al., 2024)
2	Digital circular economy: A new perspective on digitalisation as a driver for sustainability? (Klusch & Hielscher, 2025)
3	Role of Digital Transformation for Achieving Sustainability: Mediated Role of Stakeholders, Key Capabilities, and Technology (Martínez-Peláez et al., 2023)
4	Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda (Nishant et al., 2020)
5	Unleashing the convergence amid digitalization and sustainability towards pursuing the Sustainable Development Goals (SDGs): A holistic review (Del Río Castro et al., 2021)
6	The relationship between organizational culture, sustainability, and digitalization in SMEs: A systematic review (Isensee et al., 2020)

7	Exploring the fusion of greening and digitalization for sustainability (Ye et al., 2024)
8	The emergence of digitalization to the manufacturing sector in the sustainability context: A multi-stakeholder perspective analysis (Sankar et al., 2024)
9	The digitization of ESG matrix (Telukdarie et al., 2024)
10	An Integrative View of the Transformations towards Sustainability and Digitalization: The Case for a Dual Transformation (Kürpick et al., 2023)
11	When digitalization meets sustainability: exploring interactions within a manufacturing firm (Galvani et al., 2025)
12	Exploring the linkages among green digital transformation capability, ambidextrous green learning and sustainability performance: a case study of manufacturing firms in Taiwan (Huang & Huang, 2024)
13	Exploring the impact of digital knowledge, integration and performance on sustainable accounting, reporting and assurance (De Silva et al., 2025)
14	Factors in uencing the digitalization of sustainability accounting, reporting and disclosure: a systematic literature review (Valentinetti & Rea, 2025)
15	Structural and Digital Transformation of the Financial Industry: A Futuristic Approach for Sustainable and Green Digitalization (Fahad & Bulut, 2024)
16	Enabling a Sustainable Digital Transformation (Liao, 2024)
17	Digital Innovation and Sustainable Development: Two Sides of the Same Coin (De Pascale et al., 2024)
18	Digital Twins for Sustainability in the Context of Biological Transformation (Seegrün et al., 2023)
19	Digital Reset: Redirecting Technologies for the Deep Sustainability Transformation (Lange et al., 2022)
20	Digital Transformation and Environmental Sustainability: A Review and Research Agenda (Feroz et al., 2021)
21	Exploring the Nexus Between Digital Transformation and Sustainability (Apata, 2024)
22	Business models for digital sustainability: Framework, microfoundations of value capture, and empirical evidence from 130 smart city services (Bencsik et al., 2023)
23	Framework to supporting monitoring the circular economy in the context of industry 5.0: A proposal considering circularity indicators, digital transformation, and sustainability (Payer et al., 2024)
24	From Digital to AI Transformation for Sustainability (Katsamakas, 2024)
25	Incorporating Service Design for Industry 4.0: A Scientometric Review for Green and Digital Transformation Driven by Service Design (Jiang, 2020)
26	Integrating Digital Transformation and Sustainability in Manufacturing (Rahnama, 2023)
27	Capabilities for Digital Transformation and Sustainability in an Emerging Economy (Juliano et al., 2023)
28	Digital Sustainability Framework (World Bank Group, 2024)
29	Digital for Sustainability (Konstantinos et al., 2023)

30	Reaching sustainability during a digital transformation: a PLS approach (El Hilali et al., 2020)
31	Shaping Digital Transformation – Digital solution systems for the transition to sustainability (Ramesohl et al., 2021)
32	Sysematic literature review of digital and green transformation of manufacturing SMEs in Europe (Abilakimova et al., 2025)
33	The Degree of Contribution of Digital Transformation Technology on Company Sustainability Areas (Costa et al., 2022)
34	The impact of digital transformation on big data analytics and firm's sustainability performance in a post-pandemic era (Cumba et al., 2024)
35	Integrating Sustainability into the Engineering Design process using the Global Reporting Initiative Indicators (Maxwell, 2014)
36	Digital Transformation and Sustainable Performance: The Role of Management Control System (Latif et al., 2023)
37	Sustainable Digital Transformation for SMEs: A Comprehensive Framework for Informed Decision-Making (Martínez-Peláez et al., 2024)
38	IT and sustainable development - a central issue for the future (Pamlin & Thorslund, 2004)
39	Design and Validation of a Framework for Sustainable Digital Transformation in the Context of Strategic Management (Pasqual, 2023)
40	Driving Sustainable Innovation in Digital Technologies: A Deep Dive into Energy-Efficient Computing and Circular Design (Mabel, 2025)
41	The game-changing potential of digitalization for sustainability: possibilities, perils, and pathways (Seele & Lock, 2017)
42	Green growth: a bibliometric analysis of digital innovation and Sustainable Development Goals (SDGs) (John et al., 2025)
43	Driving green digital innovation in higher education: the influence of leadership and dynamic capabilities on cultivating a green digital mindset and knowledge sharing for sustainable practices (*Driving Green Digital Innovation in Higher Education: The Influence of Leadership and Dynamic Capabilities on Cultivating a Green Digital Mindset and Knowledge Sharing for Sustainable Practices | BMC Psychology*, n.d.)
44	A framework for mapping potential sustainability impact of digitalization solutions (Lövehagen, 2023)
45	The Need for New Product Development Capabilities from Digitalization, Sustainability, and Servitization Trends (Hallstedt et al., 2020)
46	Towards Sustainable Digital Innovation of SMEs from the Developing Countries in the Context of the Digital Economy and Frugal Environment (Yousaf et al., 2021)
47	Self-Assessment Framework for Corporate Environmental Sustainability in the Era of Digitalization (Eisner et al., 2022)
48	Impact of Digital Transformation toward Sustainable Development (Alojail & Khan, 2023)

49	Sustainable Digital Transformation Roadmaps for SMEs: A Systematic Literature Review (Mick et al., 2024)
50	Understanding Innovation and Sustainability in Digital Organizations: A Mixed-Method Approach (Schork et al., 2025)
51	A Study on the Impact of Corporate Digital Transformation on Environmental, Social, and Governance (ESG) Performance: Mechanism Analysis Based on Resource Allocation Efficiency and Technological Gap (Sang et al., 2025)
52	Enhancing Digital Innovation for the Sustainable Transformation of Manufacturing Industry: A Pressure-State-Response System Framework to Perceptions of Digital Green Innovation and Its Performance for Green and Intelligent Manufacturing (Yin et al., 2022)
53	How Digitalization and Sustainability Promote Digital Green Innovation for Industry 5.0 through Capability Reconfiguration: Strategically Oriented Insights (Xu et al., 2024)
54	Digital sustainable entrepreneurship: A business model perspective on embedding digital technologies for social and environmental value creation (Gregori & Holzmann, 2020)
55	Digital sustainability: basic conditions for sustainable digital artifacts and their ecosystems (Stuermer et al., 2017)

Table A1: Reference Number Toward Article

Theme	Drivers	Description
1. Sustainable Data Analytics & AI	Inter-Organizational Data Ecosystems (Ref: 17, 26, 54)	Participation in shared data ecosystems or platforms promoting sustainability-by-design approaches. DCT (sensing); Institutional Theory (normative)
	Regulatory and Standardization Pressures (Ref: 2, 19, 21, 23, 38)	External regulatory mandates and industry standards driving integration of sustainable data practices. Institutional Theory (coercive, Normative)
	Stakeholder and Societal Expectations (Ref: 2, 3, 11, 15, 31, 46, 49, 53, 54, 55)	Customer and stakeholder pressures influencing firms to embed sustainability into data processes. Institutional Theory (normative); RBV (Reputation as intangible resource)
	Technological Advancements and Innovation Pressure (Ref: 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 15, 16, 17, 19, 20, 21, 22, 23, 24, 26, 27, 28, 29, 30, 31, 32, 33, 34, 36, 37, 39, 41, 42, 43, 45, 46, 47, 48, 49, 51, 52, 53, 54, 55)	External technological trends such as AI and big data analytics enabling proactive sustainability design. DCT (sensing, seizing)

2. Strategic DT Alignment	Inter-Organizational Data Ecosystems (Ref: 3, 5, 13, 19, 21, 24, 28, 29, 31, 37, 41, 45, 48, 50)	Data-sharing platforms and ecosystem collaborations promote sustainable-by-design transformation through shared capabilities. DCT (sensing); Institutional Theory (normative)
	Regulatory and Policy Pressures (Ref: 3, 8, 10, 13, 14, 15, 16, 19, 21, 27, 28, 30, 32, 37, 38, 39, 40, 41, 45, 48)	External policies, regulations, and standards push organizations to reconfigure data practices for sustainability. Institutional Theory (coercive, normative)
	Stakeholder and Societal Expectations (Ref: 3, 5, 8, 10, 13, 14, 15, 16, 19, 21, 23, 24, 25, 27, 28, 30, 32, 33, 34, 36, 37, 38, 39, 40, 41, 45, 48)	Expectations from external stakeholders increase pressure on organizations to embed sustainability in digital data strategies. RBV (valuable), Institutional Theory (normative);
	Technological Advancements and Innovation Pressure (Ref: 3, 5, 8, 10, 11, 13, 14, 15, 16, 18, 19, 21, 22, 23, 24, 25, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 44, 45, 47, 48, 49, 50, 51, 53, 55)	Technological advancements and digital innovations enable organizations to embed ESG principles into data practices. DCT (sensing, seizing, reconfiguring); RBV (valuable, rare)
3. Digital Capability Building & Learning	Inter-Organizational Data Ecosystems (Ref: 7, 12, 15, 24, 26, 28, 42, 43, 46, 54)	Inter-organizational platforms and data-sharing ecosystems drive co-developed sustainability practices and circular data flows. DCT (sensing); Institutional Theory (normative)
	Regulatory and Policy Pressure (Ref: 6, 7, 15, 12, 24, 28, 33, 35, 36, 40, 42, 43, 44)	External policies, regulations, and industry standards compel organizations to embed sustainability into digital data practices. Institutional Theory (coercive, normative)
	Stakeholder and Societal Expectations (Ref: 6, 7, 12, 15, 16, 19, 20, 24, 26, 28, 33, 35, 36, 42, 43, 44)	External stakeholders including customers, communities, and investors exert normative pressure for sustainable data practices and transparency. RBV (valuable); Institutional Theory (normative);
	Technological Advancements and Innovation Pressure (Ref: 3, 6, 7, 10, 11, 12, 13, 15, 16, 18, 19, 20, 22, 24, 25, 26,	Emerging digital technologies and tools act as external enablers for organizations to implement sustainability-by-design in data practices. DCT (sensing, seizing); RBV (valuable)

	27, 28, 30, 32, 33, 35, 36, 38, 40, 42, 43, 44, 45, 46, 47, 49, 50, 51, 52, 53, 54)	
4. Circular Data Resource Management	Inter-Organizational Data Ecosystems (Ref: 2, 12, 24, 31, 51, 54)	Collaborative data platforms and inter-organizational networks foster shared digital infrastructure for circularity. DCT (sensing); Institutional Theory (normative)
	Regulatory and Policy Pressures (Ref: 2, 18, 19, 26, 29, 31, 38, 39, 45)	External policies, regulations, and compliance standards push organizations to integrate traceability and circularity in data systems. Institutional Theory (coercive, normative)
	Stakeholder and Societal Expectations (Ref: 2, 4, 18, 19, 26, 29, 31, 33, 39, 45, 47)	Market and societal stakeholders increase demands for transparent and sustainable data handling across product lifecycles. Institutional Theory (normative); RBV (valuable)
	Technological Advancements and Innovation Pressure (Ref: 2, 4, 6, 7, 11, 13, 14, 16, 18, 19, 20, 22, 23, 24, 26, 29, 31, 33, 34, 36, 37, 38, 39, 42, 44, 45, 47, 49, 50, 51, 52, 54, 55)	Emerging technologies such as AI, big data, and digital product passports enable organizations to operationalize circular data practices. DCT (sensing, seizing, reconfiguring); RBV (valuable, rare)
5. Data Integration & Interoperability	Inter-Organizational Data Ecosystems (Ref: 10, 17, 24, 46, 50)	Data-sharing platforms and ecosystem collaborations promote sustainable-by-design transformation through shared capabilities. DCT (sensing); Institutional Theory (normative)
	Regulatory and Policy Pressures (Ref: 10, 14, 20, 21, 35, 36, 38, 39, 40, 50, 53, 54)	External policies, regulations, and standards push organizations to reconfigure data practices for sustainability. Institutional Theory (coercive, normative)
	Stakeholder and Societal Expectations (Ref: 6, 10, 14, 15, 20, 24, 26, 35, 36, 38, 39, 40, 42, 43, 48, 50, 53, 54)	Expectations from external stakeholders increase pressure on organizations to embed sustainability in digital data strategies. RBV (valuable); Institutional Theory (normative)
	Technological Advancements and Innovation Pressure (Ref: 3, 4, 6, 10, 14, 15, 17, 20, 21, 22, 23, 24, 26, 27, 29, 30,	Technological advancements and digital innovations enable organizations to embed ESG principles into data practices. DCT (sensing, seizing, reconfiguring); RBV (valuable, rare)

	32, 34, 35, 36, 38, 39, 40, 42, 43, 44, 46, 48, 49, 50, 53, 54, 55)	
6. Energy Efficiency & Real Time Optimization	Inter-Organizational Data Ecosystems (Ref: 3, 17, 23, 31, 46)	Data-sharing platforms and ecosystem collaborations promote sustainable-by-design transformation through shared capabilities. DCT (sensing); Institutional Theory (normative)
	Stakeholder and Societal Expectations (Ref: 3, 7, 17, 19, 33, 42)	Expectations from external stakeholders increase pressure on organizations to embed sustainability in digital data strategies. RBV (valuable); Institutional Theory (normative)
	Technological Advancements and Innovation Pressure (Ref: 3, 4, 6, 7, 10, 11, 13, 15, 16, 17, 19, 20, 21, 22, 23, 25, 26, 31, 33, 35, 40, 42, 44, 46, 47, 49, 51, 52, 53, 54)	Technological advancements and digital innovations enable organizations to embed ESG principles into data practices. RBV (valuable, rare); DCT (sensing, seizing, Reconfiguring)
7. Governance & ESG Reporting	Regulatory and Policy Pressures (Ref: 9, 13, 24, 29, 37, 42, 50, 51)	External policies and ESG disclosure mandates pressure firms to digitize and standardize data governance for compliance. Institutional Theory (coercive, normative)
	Stakeholder and Societal Expectations (Ref: 9, 13, 24, 29, 37, 39, 42, 43, 48, 50, 51, 53)	Normative pressures from investors and society increase ESG transparency and responsible data stewardship. RBV (valuable); Institutional Theory (normative)
	Technological Advancements and Innovation Pressure (Ref: 9, 13, 24, 29, 36, 37, 39, 43, 48, 50, 51, 53)	Technological tools such as NLP and ML enable scalable, real-time ESG data extraction and automated reporting systems. DCT (sensing, reconfiguring); RBV (valuable, rare)

Table B1: External Drivers

Enablers & Brief Description	**Seven-Theme Explanation**
E1 Data-Driven Organizational Culture – A company-wide mindset that treats data (incl. ESG metrics) as the basis for every decision and	#1 Culture encourages staff to trust analytics & AI for eco-innovation. #2 Shared data mindset keeps all units aligned with green DT goals.

innovation effort. (Ref: 1, 2, 3, 4, 5, 6, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19, 20, 22, 23, 24, 25, 27, 28, 29, 30, 31, 32, 34, 35, 36, 37, 38, 39, 42, 43, 49, 50, 51, 55)	#3 Continuous learning norms reinforce data skills and literacy. #4 Values lean, non-duplicative data storage & reuse. #5 Silo-breaking culture promotes enterprise data sharing. #6 Openness to real-time data enables rapid energy fine-tuning. #7 Integrity norm drives accurate, transparent sustainability data. DCT (sensing, seizing); RBV (valuable); Institutional Theory (normative)
E2 Data Governance & Quality Management – Formal policies, roles, and controls that safeguard data integrity, ethics, security, and compliance. (Ref: 1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 23, 24, 25, 26, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 54, 55)	#1 Guarantees reliable datasets for advanced sustainability analytics/AI. #2 Aligns data controls with DT roadmap & ESG targets. #3 Clarifies stewardship roles, improving data-skills development. #4 Lifecycle rules cut redundant storage, aiding circularity. #5 Standards ease cross-system data exchange. #6 Policies cover secure IoT data streams for real-time optimization. #7 Provides auditable, compliant data for ESG disclosure. RBV (valuable); Institutional Theory (coercive, normative)
E3 Advanced Data Analytics Capabilities – In-house tools, platforms, and talent for big-data, AI, and predictive modelling focused on sustainability value. (Ref: 1, 2, 3, 4, 5, 7, 9, 10, 11, 12, 13, 14, 18, 19, 20, 21, 23, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 38, 39, 40, 42, 43, 44, 45, 46, 47, 49, 50, 51, 52, 53, 55)	#1 Uses ML to uncover carbon-reduction or circular-economy insights. #2 Supplies evidence to steer DT investments toward green outcomes. #3 Builds analytics expertise via ongoing up-skilling programs. #4 Detects resource waste & optimize reuse pathways. #5 Requires clean, integrated data from multiple systems. #6 Processes IoT feeds to auto-tune energy use in real time. #7 Automates KPI dashboards for robust ESG reporting. DCT (sensing, seizing); RBV (valuable)
E4 Integrated Data Infrastructure – Unified architecture & platforms that let sustainability data flow seamlessly across applications and business units. (Ref: 1, 2, 7, 9, 10, 11, 12, 13, 14, 16, 17, 18, 20, 21, 23, 27, 28, 32, 33, 34,	#1 Central hub feeds analytics & AI with holistic data sets. #2 One "source of truth" anchors strategy execution on shared ESG KPIs. #3 Integration projects grow cross-functional data skills.

36, 37, 38, 42, 43, 45, 48, 49, 50, 51, 43, 44)	#4 Consolidation removes duplicate databases, saving resources. #5 Implements interoperability standards enterprise-wide. #6 Streams IoT data instantly to optimization engines. #7 Simplifies company-wide ESG data aggregation & assurance. DCT (reconfiguring); RBV (valuable)
E5 Data Transparency & Performance Reporting – Open sharing of sustainability performance data, internally and with stakeholders, to foster accountability and continual improvement. (Ref: 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 55)	#1 Public KPI dashboards spur analytic scrutiny & AI-driven fixes. #2 Transparent metrics keep DT efforts aligned with stated green goals. #3 Feedback loops teach teams to refine data and processes. #4 Visibility highlights material flows, encouraging circular actions. #5 Necessitates standard formats for interoperable disclosures. #6 Real-time reporting of IoT energy data drives swift optimization. #7 Meets regulatory & investor demands for credible ESG information. DCT (sensing, seizing); RBV (valuable); Institutional Theory (normative/, coercive)
E6 Employee Data Literacy & Training – Continuous programs that build workforce skills to access, analyze, and act on sustainability-related data.(Ref: 1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 14, 17, 19, 20, 23, 27, 28, 29, 30, 32, 33, 34, 35, 36, 39, 43, 45, 47, 48, 49, 51, 53, 55)	#1 Upskilled staff can develop AI/analytics for greener outcomes. #2 Training embeds sustainability KPIs into everyday digital tasks. #3 Enhances adaptive capacity through lifelong learning culture. #4 Teaches efficient data storage & reuse practices. #5 Equips teams to work with integrated, interoperable data tools. #6 Builds know-how to configure IoT/real-time systems for energy savings. #7 Improves data accuracy & compliance in ESG reporting workflows. DCT (reconfiguring); RBV (valuable)

Table B2: Organizational Enablers

Note: #1. Sustainable Data Analytics & AI, #2 Strategic DT Alignment, #3 Digital Capability Building, #4 Circular Data Resource Management, #5 Data Integration & Interoperability, #6 Energy-Efficiency & Optimization, #7 Governance & ESG Reporting

DCT	**Level 1: Foundational Data Practices**	**Level 2: Integrated Data Practices**	**Level 3: Transformative Data Practices**
Sensing (ability to sense and identify opportunities/threats)	**Basic internal data monitoring:** Capabilities focus on collecting and monitoring data from internal operations. Analytics are minimal (simple descriptive reports) and used reactively rather than for proactive insight. *Sustainability-by-design:* Sustainability is only a minor consideration at this stage (limited to compliance reporting of environmental data), not inherently built into data collection processes. (Ref: 5, 6, 7, 8, 9, 11, 13, 14, 17, 18, 19, 20, 21, 22, 23, 24, 25, 27, 29, 30, 3, 32, 33, 35, 37, 38, 42, 44, 47, 50, 51, 52, 53, 54)	**Multi-source data sensing:** Capabilities expand to systematically gather data from diverse sources (internal databases, market research, customer feedback, even some external sensor or partner data). Analytics become more advanced (trend analysis, dashboards) to identify emerging trends. Data platforms are increasingly integrated across the enterprise, enabling broader insights. *Sustainability-by-design:* Sustainability metrics (e.g. energy usage, emissions, social impact data) are now included by design in data collection and analysis, so the organization begins identifying opportunities with sustainability benefits as part of its sensing activities. (Ref: 1, 3 7, 9, 10, 13, 14, 15, 17, 18, 19, 20, 21, 12, 22, 23, 24, 26, 27, 28, 29, 30, 32, 33, 34, 36, 38, 39, 40, 42, 46, 47, 48, 49, 50, 51, 52, 53, 54)	**Real-time intelligent sensing:** Highly advanced capabilities leverage real-time big data and AI for environmental scanning (e.g. IoT sensors, social media and market intelligence feeds). The organization continuously detects and interprets emerging opportunities or risks with sophisticated analytics (machine learning models, predictive insights). *Sustainability-by-design:* fully embedded – the data ecosystem captures comprehensive environmental and social indicators in real time, ensuring that the firm's sensing of new opportunities inherently factors in sustainability goals (e.g. spotting green market trends or climate risks as part of opportunity identification). (Ref: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 12, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39,

			40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55)
Seizing (ability to seize opportunities with data-driven decisions)	**Ad-hoc data usage in decisions:** Capabilities for data-driven decision-making are very limited. Management relies mostly on experience and basic periodic reports to seize opportunities. Data is used retrospectively (to justify or review decisions) rather than to drive strategy in real-time. *Sustainability-by-design:* Sustainability considerations at this level are ad hoc or compliance-driven (e.g. meeting regulations), and are not actively factored into how opportunities are evaluated or pursued. (Ref: 8, 11, 19, 23, 27, 30, 32, 34, 36, 42, 52.)	**Data-informed decision-making:** The organization develops capabilities to use data analytics in planning and investment decisions. Business intelligence tools and predictive analytics start guiding which opportunities to pursue and how to allocate resources. Data-driven initiatives (e.g. optimizing a process or improving customer targeting) are executed across departments, reflecting a more proactive stance. *Sustainability-by-design:* Sustainability is now embedded in the decision framework — data on environmental and social impacts is considered alongside financial metrics when selecting opportunities and designing new initiatives. The company actively uses data (like carbon footprint analysis or social impact scores) to ensure projects and products are chosen and shaped with sustainable outcomes in mind. (Ref: 2, 3 6, 7,	**Fully data-driven opportunity capture:** The firm has an advanced capability to seize opportunities quickly based on data-driven insights. Strategic decisions and innovations are guided by real-time data, advanced analytics, and AI recommendations (e.g. launching new digital products or pivoting business models based on predictive modeling). The organization excels at converting data insights into swift action and market offerings. *Sustainability-by-design* is central at this stage — every new business initiative or innovation is co-created with sustainability criteria from the outset. The firm uses data to optimize strategies for both economic value and sustainability (for example, employing scenario simulations that include climate impact or using AI to design products that maximize recyclability and minimize waste). (Ref: 2, 3 4, 5, 6, 7, 8,

		9, 11, 12, 13, 14, 15, 18, 19, 20, 21, 22, 23, 24, 26, 27, 28, 29, 30, 31, 32, 33, 34, 36, 37, 38, 39, 40, 41, 42, 43, 44, 46, 47, 48, 49, 50, 51, 52, 53, 54.)	9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55)

Table B3: DCT Data-Driven Maturity Framework

DCT	Level 1: Foundational Data Practices	Level 2: Integrated Data Practices	Level 3: Transformative Data Practices
Reconfiguring (ability to reconfigure/transform the organization and its resources)	**Rigid data systems, low agility:** The organization's data infrastructure and processes are siloed and inflexible, making it hard to adapt or reconfigure in response to change. Digital transformation efforts are piecemeal and slow due to legacy systems and a lack of change capabilities. *Sustainability-by-design:* is largely absent at this stage – data systems and processes are designed without considering sustainability (beyond basic regulatory compliance), meaning opportunities to improve energy efficiency or reduce waste in IT/operations are mostly overlooked. (Ref: 1, 2, 3, 15, 18, 19, 20, 23, 26, 28, 31, 37, 45, 52)	**Adaptive infrastructure and processes:** The organization builds more agile data capabilities by modernizing IT (e.g. adopting cloud platforms, data integration tools) and streamlining processes. It can reconfigure or scale its data systems more easily to support new digital initiatives. Cross-functional teams and continuous improvement practices (like agile and DevOps methods) start to take hold, improving the capacity to reorganize and innovate. *Sustainability-by-design:* principles are gaining traction — when processes or systems are redesigned, the firm now factors in sustainability (for instance, optimizing data center usage for energy efficiency, digitizing paper-based workflows to cut waste, or choosing software solutions that facilitate circular economy practices).	**Continuously reconfigurable & sustainable-by-design organization:** The firm possesses dynamic capabilities to continually transform its data architecture and organizational setup in response to evolving technology and market demands. IT systems are highly modular and scalable (e.g. microservices, API-driven ecosystems), allowing rapid integration of new tools or data sources and frequent restructuring of processes. The organization embraces a culture of continuous digital transformation and innovation. *Sustainability-by-design:* is fully institutionalized in reconfiguration efforts — any structural or system change is guided by sustainable design principles. For example, the enterprise deploys green IT infrastructure (energy-efficient, powered by renewables), implements circular IT

		These considerations are becoming a routine part of reconfiguration projects. (Ref: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55)	asset management (reusing/recycling hardware), and aligns all process changes with long-term environmental and social governance (ESG) objectives. Every adaptation in the organization thus advances both digital capability and sustainability concurrently. (Ref: 1, 2, 3, 4, 5, 6, 7, 9, 11, 12, 13, 15, 16, 17, 18, 19, 21, 22, 23, 24, 25, 26, 27, 28, 30, 31, 32, 36, 37, 38, 39, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53)

RBV Dimension	Level 1: Emergent Data Stewardshipad-hoc, silo-bound practices	Level 2: Systematic Data Governanceenterprise alignment & control	Level 3: Regenerative Data Ecosystemsustainable-by-design, continuously adaptive
Value	Basic ICT infrastructure is stood up to **collect and share operational data**, but usage is project-specific and sustainability insights are still incidental. (e.g., "technology plays a critical role … providing the tools … to collect, analyse, and disseminate data"). (Ref: 2, 3, 6, 7, 9, 14, 16, 17, 23, 28, 29, 31, 34, 37, 38, 46, 47, 48, 50, 55)	Firm adopts **standardised interfaces that give persistent referencing of life-cycle inventory (LCI) data**, so data can routinely inform performance and ESG reporting across functions. (Ref: 1, 6, 9, 11, 13, 14, 20, 24, 28, 29, 35, 37, 45, 50, 51, 52)	A **digital product passport (DPP)** stores full provenance plus "instructions for reuse, repair, disassembly and recycling," turning data into *continual* economic and environmental value. (Ref: 1, 2, 7, 19, 23, 24, 25, 26, 28, 29, 31, 37, 40, 49, 51, 53, 54, 55)
Rarity	An *expandable mapping* links product design concepts to life-cycle (LC) data, creating an **organisation-specific dataset** that competitors do not yet have. (Ref: 1, 11, 13, 18, 20, 26, 28, 31, 35, 38, 45, 49, 50, 55)	SMEs develop *Green-ICT* capabilities and governance; proprietary sustainability metrics accumulate, giving the firm a **distinct data portfolio** hard to source elsewhere. (Ref: 3, 6, 10, 11, 13, 26, 28, 31, 37, 44, 46, 47)	AI/ML pipelines mine multi-source operational + ESG streams, surfacing **unique circular-economy insights** that were "otherwise trapped" in unstructured data—rare in the industry. (Ref: 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55)
Inimitability	A nascent **semantic schema** connects design attributes to LC impacts; know-how is still emerging but starts to raise	**End-to-end CAD-ERP-MES integration** embeds sustainability attributes; replication requires both technical depth and cross-functional change, making	**Automated feature extraction** pulls LC data directly from design models, creating a self-reinforcing knowledge base and tacit expertise that rivals struggle

	imitation barriers. (Ref: 1, 21)	imitation costly. (Ref: 1, 3, 6, 9, 12, 14, 17, 18, 20, 22, 23, 28, 31, 33, 37, 38, 39, 46, 50, 52)	to copy. (Ref: 1, 3, 9, 13, 14, 33, 47)
Organised to Exploit	Ecological **"master / shadow" data** are stored, yet exploitation is uncoordinated; sustainability data sit in isolated repositories. (Ref: 18, 45)	Trustworthy access controls plus linked data structures let multiple actors **share and act on sustainability data**, so governance mechanisms actively exploit the resource. (Ref: 2, 3 16, 26, 28, 29, 31, 47, 48, 55)	**Semantically-described LCA knowledge is continuously updated and embedded in workflows**, ensuring the whole organisation (and partners) exploits data for ongoing circular innovation. (Ref: 1, 12, 26, 28, 43, 46, 48, 55)

Table B4.1: RBV Data-Driven Maturity Framework

NRBV	**Level 1: Reactive & Compliance-DrivenMinimal ESG integration in data (ad-hoc, efficiency for compliance)**	**Level 2: Proactive & IntegratedStrategic inclusion of sustainability in data practices**	**Level 3: Sustainable-by-DesignData systems inherently designed for sustainability**
Pollution Prevention(Internal efficiency & waste reduction)	**Reactive data efficiency:** Basic optimization of data operations to cut "digital waste" (e.g. eliminating redundant data storage, improving server utilization) primarily for cost reduction or compliance. (Ref: 12, 16, 17, 18, 21, 23, 31, 36, 37)	**Continuous data-driven efficiency:** Proactive use of data analytics for ongoing process improvement to minimize resource and energy use in IT operations, embedding environmental performance metrics into internal data management practices. (Ref: 3, 6, 7, 9, 12, 15, 16, 17, 20, 21, 22, 29, 3, 31, 34, 36, 42, 47, 48, 53)	**Green data architecture by design:** Data infrastructure and algorithms are designed upfront for minimal environmental footprint (e.g. energy-efficient computing, renewable-powered data centers), making sustainability an inherent criterion in system design and data governance. (Ref: 3, 6, 8, 9, 10, 12, 13, 14, 15, 16, 20, 21, 23, 24, 27, 28, 29, 30, 31, 32, 35, 37, 43, 44, 45,

			47, 48, 49, 51)
Product Stewardship*(Stakeholder & lifecycle integration)*	**Compliance-focused transparency:** Reactive sharing of essential ESG data with external stakeholders to meet regulations or market pressure (e.g. publishing required sustainability metrics, basic product impact data) with no further integration. (Ref: 3, 7, 9, 13, 17, 18, 23, 29, 37, 42, 49, 53)	**Integrated lifecycle data stewardship:** Systematic collection and use of product lifecycle data across the supply chain to improve sustainability (e.g. tracking carbon footprint, material sourcing data) and actively sharing this information with partners and customers to collaboratively reduce environmental impact. (Ref: 1, 2, 3, 6, 10, 11, 12, 13, 17, 18, 20, 21, 23, 25, 26, 29, 35, 37, 38, 42, 45, 47, 48, 49, 51, 53)	**Sustainable-by-design product data innovation:** Data-driven product and service development that inherently includes stakeholder input and ESG criteria from the start (e.g. using real-time usage and impact data to co-create circular products), thus enabling full transparency and sustainability co-creation as a built-in feature of offerings. (Ref: 1, 3, 7, 16, 17, 18, 19, 20, 22, 26, 29, 35, 37, 38, 42, 45, 49, 53.)
Sustainable Development*(Future-oriented sustainable innovation)*	**Ad-hoc sustainable data initiatives:** Isolated or pilot projects using data for sustainability goals (e.g. one-off analytics for energy saving or community benefit), largely philanthropic or compliance-oriented and not integrated into core strategy. (Ref: 1, 3, 7, 16, 17, 18, 19, 20, 22, 26, 29, 35, 37, 38, 42, 45, 49, 53)	**Strategic sustainable data programs:** Alignment of data initiatives with long-term sustainability goals (e.g. employing big data to identify new green business opportunities or using IoT data to enhance resource efficiency), signaling a shift to making sustainability a key driver in digital strategy and innovation. (Ref: 3, 4, 5, 7, 9, 12, 13, 15, 16, 17, 19, 20, 22, 23, 24, 25, 26, 27, 30, 31, 32, 34, 42, 43, 45, 47, 49, 51, 52, 53)	**Transformative sustainability-by-design innovation:** Fully embedding ESG goals into digital innovation – developing new data-driven platforms, AI solutions, or business models that by design deliver environmental and social value (for example, data platforms for circular economy or AI optimizing city-wide resource use), thus positioning sustainability as a

			fundamental outcome of digital transformation. (Ref: 3, 12, 14, 15, 21, 24, 25, 26, 27, 28, 29, 30, 31, 32, 34, 36, 43, 48, 49, 51, 53, 54)

Table B4.2: NRBV Data-Driven Maturity Framework

Institutional Pressure	**Level 1: Foundational Data Governance**	**Level 2: Integrated Data Governance**	**Level 3: Transformative Data Governance**
Coercive (Regulatory)	Implement basic ESG data governance policies to ensure compliance with mandatory sustainability reporting and data protection regulations, embedding these requirements into core data processes. (Ref: 2, 3, 15, 19, 20, 26, 28, 37, 38, 40, 42, 44, 45)	Systematically embed regulatory compliance into data governance; processes are standardized to capture and monitor ESG metrics in line with evolving regulations, moving from ad hoc to routine compliance checks. (Ref: 1, 8, 9, 13, 14, 19, 20, 26, 36, 42)	At the advanced stage, data practices are fully aligned with and often exceed ESG regulatory standards; the organization proactively monitors sustainability data and even helps shape future regulations by demonstrating best-in-class governance. (Ref: 1, 8, 9, 12, 13, 14, 15, 19, 21, 24, 29, 33, 34, 35, 36, 37, 39, 40, 41, 43, 47, 49, 50, 51, 52, 53, 55)
Normative (Standards)	Adopt baseline industry sustainability data standards; at this nascent stage, data practices begin aligning with common ESG frameworks to satisfy professional norms, albeit in a rudimentary fashion. (Ref: 1, 3, 6, 9, 37, 45)	Integrate recognized ESG data governance standards and certifications into operations; sustainable data management becomes part of professional practice as staff are trained and processes certified to industry norms. (Ref: 7, 20, 28, 37, 43, 48)	Lead industry norms for sustainable data governance; the organization helps set emerging standards (e.g., via industry consortia) such that sustainable data practices are fully institutionalized and the firm serves as a model for peers. (Ref: 1, 2, 3, 5, 6, 7, 8, 9, 12, 14, 15, 16, 19, 24, 26, 28, 29, 31, 33, 35, 37, 38, 39, 41, 43, 45, 48, 49, 50, 52, 53, 55)
Mimetic	Benchmark against	Proactively adopt and	Continuously emulate and

(Peer Influence)	peers' sustainable data initiatives and imitate simple best practices; for example, adopt basic sustainability dashboards or reporting techniques similar to those of industry leaders. (Ref: 3, 8, 9, 12, 16, 19, 26, 39, 55)	adapt proven sustainable data practices from leading firms; the organization regularly benchmarks its ESG data management against peers and implements advanced tools (e.g., analytics for ESG performance) based on successful external examples. (Ref: 1, 2, 3, 6, 8, 9, 15, 19, 20, 24, 26, 28, 31, 37, 39, 42, 43, 45, 48, 55)	refine cutting-edge sustainable data innovations observed across the industry; the firm rapidly implements new ESG data approaches pioneered by others, staying at the forefront and becoming a benchmark that peers emulate. (Ref: 1, 2, 3, 4, 5, 6, 8, 9, 10, 12, 13, 14, 15, 16, 18, 19, 20, 24, 26, 28, 29, 31, 33, 35, 37, 39, 40, 42, 43, 45, 48, 52, 55)

Table B5: Institutional Theory Data-Driven Maturity Framework

Theme	**Target**	**Explanation**
G1: Sustainable Data Analytics & AI	G1-1: Implement energy-efficient (Green) AI and analytics models (Ref: 4, 7, 10, 13, 16, 19, 21, 23, 31, 32, 40, 45)	Design AI models and data analytics pipelines to minimize energy use and carbon emissions (e.g. choosing efficient algorithms and using renewable-powered computing). This reduces the carbon footprint of data-driven processes while aligning analytics innovation with environmental goals. DCT (seizing); RBV (valuable, inimitability)
	G1-2: Embed ESG metrics into data analysis and AI models (Ref: 1, 3, 4, 5, 9, 12, 13, 14, 16, 17, 18, 19, 20, 21, 12, 26, 29, 3, 33, 34, 36, 42, 48, 50, 51)	Incorporate environmental and social indicators (like emissions or waste) into analytics and AI decision processes so that data insights directly measure sustainability performance. This integrates sustainability criteria into data modeling and reporting. DCT (sensing); RBV (value); Institutional Theory (normative)
	G1-3: Use AI and analytics to optimize resource efficiency (Ref: 3, 4, 5, 7, 10, 13, 14, 15, 16, 17, 18, 19, 21, 12, 22, 23, 26, 29, 30, 3, 31, 32, 33, 34, 36, 37, 40, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53)	Apply data-driven optimization (e.g. ML-based scheduling) to improve operational sustainability. For example, use analytics to reduce energy and material waste in production or logistics, aligning digital processes with environmental objectives. DCT: seizing; RBV/NRBV: value
G2: Strategic	G2-1: Align enterprise	Every new or updated data platform, pipeline, or

Digital-Transformation Alignment	data strategy with sustainability goals (Ref: 7, 9, 13, 14, 19, 29, 40, 51)	dataset must (i) carry carbon/energy metadata, (ii) run on low-carbon or renewable-powered infrastructure, and (iii) support ESG-analytics use-cases. Roadmaps for data lakes, warehouses, streaming, and AI pipelines are prioritized by their projected reduction of data-center emissions and storage overhead. DCT (seizing); RBV (valuable); Institutional Theory (normative, coercive)
	G2-2: Embed ESG data-KPIs in digital-project approval (Ref: 7, 9, 12, 28, 29, 32, 35, 36, 38, 39, 40, 44, 47, 48, 51, 52, 53)	Include sustainability metrics (e.g. energy savings, emissions reduction) alongside financial ROI when evaluating digital projects. Only approve initiatives that demonstrate both business value and environmental benefit. DCT (sensing); RBV (valuable); Institutional (normative)
	G2-3: Create data-governance bodies that enforce sustainability-by-design (Ref: 2, 7, 9, 13, 14, 17, 18, 19, 28, 464, 34, 35, 36, 38, 40, 43, 44, 47, 53, 55)	Establish a 'Green Data Steering Committee' (CIO, Chief Data Officer, ESG lead) that audits data schemas, storage tiers, and analytics workloads for energy intensity and ESG-data quality. The committee can veto data initiatives if lifecycle assessments or data-minimization plans are inadequate. DCT (reconfiguring); RBV (valuable); Institutional Theory (normative)
G3: Digital Capability Building & Learning	G3-1: Provide training on sustainable data practices to employees (Ref: 6, 7, 10, 11, 12, 13, 12, 28, 33, 36, 43, 45, 47, 53)	Train staff in green data management, ethical AI, and ESG analytics. For example, teach developers how to optimize code for energy efficiency and include sustainability factors in data work. This builds internal capability to implement sustainable-by-design practices. DCT (reconfiguring); RBV (valuable); Institutional Theory (normative)
	G3-2: Foster collaboration between IT/data and sustainability teams (Ref: 3, 5, 7, 8, 10, 11, 12, 13, 16, 12, 26, 28, 29, 31, 32, 36, 37, 38, 42, 43, 45, 48, 49, 51, 53)	Encourage joint projects and knowledge-sharing between digital teams and environmental experts. Cross-disciplinary learning helps data experts understand sustainability needs and enables sustainability teams to leverage data tools, building sensing and seizing capabilities. DCT (sensing, seizing); RBV (valuable); Institutional Theory (normative)
	G3-3: Include sustainability in	Integrate environmental knowledge and data sustainability into digital job roles and training

	digital skill development and hiring (Ref: 3, 6, 10, 11, 12, 13, 17, 12, 27, 28, 33, 36, 43, 45, 47, 48)	programs. For example, require understanding of ESG frameworks for IT positions so that talent can apply data solutions in a sustainable context. RBV (valuable, rare); Institutional Theory (normative)
G4: Circular Data Resource Management	G4-1: Implement data lifecycle management for reuse and minimal waste (Ref: 1, 2, 7, 9, 13, 14, 19, 22, 23, 28, 29, 30, 31, 34, 36, 38, 39, 47, 50, 55)	Manage data from creation to disposal with emphasis on reuse and deduplication. For example, archive outdated data responsibly and securely delete obsolete records, treating data as a resource that circulates rather than becoming digital waste. DCT (reconfiguring); RBV (valuable, rare)
	G4-2 Consolidate data silos with shared platforms (Ref: 1, 2, 9, 10, 13, 19, 23, 24, 28, 30, 34, 36, 45, 46, 47, 50, 54)	Use unified data platforms (e.g. data lakes) and APIs so that each dataset is created once and reused across departments. This prevents redundant storage and ensures data is circulated efficiently across the organization. DCT (seizing); RBV (valuable, inimitability)
	G4-3 Minimize unnecessary data collection and storage (Ref: 19, 16, 31, 4, 42, 5)	Collect and store only data needed for sustainability purposes, applying privacy-by-design and minimization principles. This reduces energy use and waste associated with storing excess or irrelevant data. RBV (valuable); Institutional Theory: (coercive)
G5: Data Integration & Interoperability	G5-1 Adopt open data standards and APIs for ESG data (Ref: 2, 9, 10, 13, 14, 19, 28)	Implement common data formats and interoperable APIs (e.g. for emissions, energy use) so sustainability and operational data can be easily combined across systems. This ensures seamless sharing and broader use of ESG data. Institutional Theory (normative) RBV (valuable, inimitable)
	G5-2: Break down data silos by integrating sustainability data (Ref: 1, 5, 9, 13, 14, 19, 23, 28, 32, 39, 41, 47, 50, 51)	Link disparate sources (like energy, waste, supply chain) into unified platforms so that all ESG data is connected. For example, merge or interface legacy databases to create a single source of truth for sustainability metrics. DCT (reconfiguring); RBV (valuable)
	G5-3: Ensure data quality and consistency with governance (Ref: 2, 9, 13, 14, 18, 19, 35, 36, 55)	Establish rules and roles for validating, standardizing, and auditing sustainability data across systems. For example, enforce consistent units (e.g. CO_2e metrics) and definitions to make integrated data reliable for decision-making. RBV (valuable); Institutional Theory (coercive,

		normative)
G6: Energy-Efficiency & Real-Time Optimization	G6-1: Use real-time analytics to optimize data-center energy use (Ref: 7, 16, 31, 40)	Deploy sensors and monitoring to continuously measure power and adjust cooling or compute loads dynamically. By analyzing real-time usage, data centers can minimize wasteful energy consumption and improve overall efficiency. DCT (seizing); RBV (valuable)
	G6-2: Leverage edge computing to reduce transmission energy (Ref: 13, 23)	Process data locally at the edge whenever possible to avoid transmitting large data volumes to central servers. This reduces network and data-center load, saving energy in data flows while still supporting digital services. DCT (seizing); RBV (valuable)
	G6-3: Schedule compute-intensive tasks during low-carbon periods (Ref: 16, 19, 23, 31)	Align data processing (e.g. batch analytics or backups) with times when renewable energy is plentiful or demand is low. For example, run large computations on sunny/windy days or off-peak hours to minimize the carbon intensity of computing. DCT (seizing); RBV (valuable)
G7: Governance & ESG Reporting	G7-1: Establish data governance for accurate ESG reporting (Ref: 2, 5, 9, 13, 14, 19, 36, 47, 51)	Develop policies and processes to ensure sustainability data is accurate, traceable, and transparent. For example, define data ownership, validation rules, and audit trails for emissions data, embedding accountability in reporting. RBV (valuable); Institutional Theory (coercive, normative)
	G7-2: Automate ESG reporting through integrated data pipelines (Ref: 3, 9, 10, 12, 13, 14, 12, 23, 29, 33, 34, 36, 37, 38, 41, 47, 51, 55)	Connect operational systems (IoT, ERP, etc.) with analytics tools so that sustainability metrics flow automatically into reports. Automated pipelines ensure timely, accurate ESG disclosures and reduce manual errors. DCT (seizing); RBV (valuable)
	G7-3: Align ESG disclosures with standards and regulations (Ref: 2, 5, 7, 9, 13, 14, 19, 23, 36, 37, 51)	Use data management to meet frameworks like GRI or TCFD, aligning data categories and definitions with requirements. This coercive (and mimetic) alignment embeds sustainability transparency into data practices to satisfy regulatory and stakeholder expectations. RBV (valuable); Institutional Theory (coercive, mimetic)

Table B6: Targets of Data-Driven Sustainability Excellence (Goals)