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A Capability-Based Framework for Knowledge-Driven AI Innovation and Sustainability

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Abstract

As artificial intelligence (AI) technologies increasingly shape sustainability agendas, organizations face the strategic challenge of aligning AI-driven innovation with long-term environmental and social goals. While academic interest in this intersection is growing, research remains fragmented and often lacks actionable insights into the organizational capabilities needed to operationalize sustainable AI innovation. This study addresses this gap by exploring how knowledge-based organizational capabilities—such as absorptive capacity, knowledge integration, organizational learning, and strategic leadership—support the alignment of AI initiatives with sustainability strategies. Grounded in the knowledge-based view of the firm, we conduct a bibliometric and thematic analysis of 216 peer-reviewed articles to identify emerging conceptual domains at the nexus of AI, innovation, and sustainability. The analysis reveals five dominant capability clusters: (1) data governance and decision intelligence; (2) policy-driven innovation and green transitions; (3) digital transformation through education and innovation; (4) collaborative adoption for sustainable outcomes; and (5) AI for smart cities and climate action. These clusters illuminate the multi-dimensional roles that knowledge management and organizational capabilities play in enabling responsible, impactful, and context-sensitive AI adoption. In addition to mapping the intellectual structure of the field, the study proposes a set of strategic and policy-oriented recommendations for applying these capabilities in practice. The findings offer both theoretical contributions and practical guidance for firms, policymakers, and educators seeking to embed sustainability into AI-driven transformation. This work advances the discourse on innovation and knowledge management by providing a structured, capability-based perspective for designing and implementing sustainable AI strategies.

Keywords: innovation management; knowledge management; artificial intelligence; sustainability; organizational capabilities; AI-driven innovation; sustainable development; strategic alignment

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1. Introduction

The pursuit of sustainability has become a strategic imperative for organizations navigating an increasingly complex and resource-constrained global landscape. In parallel, artificial intelligence (AI) technologies have emerged as powerful drivers of innovation, enabling firms to optimize processes, enhance decision-making, and generate value across environmental, social, and economic domains [1]. While AI holds transformative potential for enhancing sustainability goals, its use often prioritizes operational efficiency—such as optimizing inventory levels, transportation routing, and demand forecasting—potentially sidelining the broader environmental and social considerations essential for long-term strategic alignment [2].

This tension raises a fundamental challenge: how can organizations ensure that AI-driven innovation meaningfully supports sustainability-oriented strategies? Addressing this question requires moving beyond technical deployments and focusing instead on the organizational capabilities that shape how technologies are selected, adapted, and integrated with broader strategic aims [3].

In this context, knowledge-based organizational capabilities provide a valuable analytical lens. Grounded in the knowledge-based view of the firm, this perspective conceptualizes organizations as repositories and processors of knowledge, where competitive advantage stems from their ability to create, integrate, and apply knowledge effectively [4]. Capabilities such as absorptive capacity [5], knowledge integration [6], organizational learning [7], and strategic leadership [8] are critical to enabling the translation of digital innovations into sustainable outcomes.

These capabilities are not purely technological, but embedded in organizational routines, culture, and structures that facilitate knowledge flow and alignment between innovation and strategy [9].

Recent developments in the AI–KM interface have sparked renewed debate on how emerging technologies reshape the dynamics between explicit and tacit knowledge within organizations. Building on Nonaka and Takeuchi's SECI model (Socialization, Externalization, Combination, Internalization), scholars have examined how AI—particularly generative AI—reshape the balance between explicit and tacit knowledge within firms. While AI can accelerate the handling and recombination of explicit knowledge [10], the creation and application of tacit knowledge remains largely dependent on human expertise, especially in contexts requiring social interaction, ethics, and judgment [11]. This reinforces the need for hybrid, capability-driven approaches that combine the strengths of AI with human sense-making in support of sustainability.

Despite growing interest in the use of AI for sustainability, the underlying organizational capability structures that enable its responsible and effective implementation remain underexplored [12]. Moreover, research at the intersection of AI, innovation management, and sustainability is fragmented, lacking an integrated framework that captures how knowledge-based capabilities support the sustainable transformation of organizations [13].

To address this gap, this study investigates the knowledge-based capabilities that enable the alignment of AI-driven innovation with sustainability strategies. Through a bibliometric and thematic analysis of 216 peer-reviewed articles, the study identifies key research trends and synthesizes five thematic clusters that together form a capability-based framework for sustainable AI innovation. These clusters reflect diverse capability domains, ranging from data governance and strategic leadership to collaboration, education, and digital infrastructure.

Accordingly, the study addresses the following research question:

What organizational capabilities are critical for aligning AI-driven innovation practices with sustainability-oriented strategies?

In line with these questions, the study pursues the following objectives:

- To identify and categorize the organizational capabilities that support the alignment of AI innovation with sustainability strategies;
- To articulate the role of knowledge management, leadership, and organizational learning in enabling this alignment;
- To map and synthesize the main research trends and capability domains through bibliometric analysis.

By addressing these objectives, the study contributes to the literature on knowledge management, innovation, and sustainability by clarifying how knowledge-intensive capabilities serve as strategic enablers of responsible and impactful AI adoption. It further offers a structured framework with practical relevance for organizations, policymakers, and educators aiming to harness AI in support of sustainable transformation. Through the application of VOSviewer and co-word analysis, this study not only maps the intellectual contours of the field but also proposes strategic directions for research and practice.

2. Literature Review

In recent years, AI has emerged as a transformative force across industries and sectors, offering unprecedented capabilities in data processing, automation, and decision-making. Parallel to this technological acceleration, global concerns around sustainability—encompassing environmental protection, social equity, and economic resilience—have intensified, driven by the urgency of climate change, resource scarcity, and rising inequality. The convergence of these two domains—AI and sustainability—presents both immense opportunities and complex challenges. Grounded in the knowledge-based view of the firm, this study assumes that organizations create value through their ability to acquire, integrate, and apply knowledge. This theoretical perspective positions organizational capabilities—such as absorptive capacity, knowledge integration, and organizational learning—as critical enablers for aligning AI innovation with sustainability goals [6].

The concept of AI sustainability-oriented strategies is gaining increasing attention, reflecting efforts to explore how AI can contribute to sustainable development goals while also considering the sustainability implications of AI itself. These strategies seek to leverage AI as a tool to support positive environmental and social outcomes and to promote responsible design, deployment, and governance practices. Within this context, KM emerges not just as a support mechanism, but as a central capability that enables organizations to transform AI-generated data into meaningful strategic actions. Research demonstrates that KM routines—such as knowledge codification, sharing, and application—are key for embedding sustainability considerations across AI projects and enhancing green innovation performance [9].

Despite growing interest, the field remains relatively fragmented, characterized by diverse conceptual frameworks, methodological approaches, and disciplinary perspectives.

When viewed through a broad lens of sustainability, several key studies stand out for their contributions to understanding its multifaceted dimensions. Bosi et al. [14] provide a comprehensive bibliometric review focused on the role of ESG factors in sustainability reporting, providing a detailed understanding of how environmental, social, and governance considerations are embedded in organizational disclosures. One study [15] presents a meta-synthesis of bibliometric reviews spanning the period from 1982 to 2019, highlighting long-term trends that are essential for constructing robust definitions of sustainability. Meanwhile, Teh et al [16] adopt an accounting and governance perspective, underscoring the relevance of institutional practices and regulatory frameworks.

When examining AI sustainability-oriented strategies, it is possible to identify a connection between broader sustainability objectives and the role of AI. In particular, the impact of AI across various sectors highlights its diverse sustainability applications in areas such as construction, transport, agriculture, health, water, and manufacturing [17]. These applications demonstrate AI's functional contributions—from environmental monitoring to circular economy solutions—spanning multiple domains.

Tabbakh et al. [18] propose a comprehensive framework for the adoption of Green AI, outlining concrete strategies that include optimization techniques, energy-efficient algorithms, and consideration of lifecycle impacts. Similarly, Zejjari et al [19] present a bibliometric analysis of the AI—sustainability research landscape, emphasizing the importance of optimization-by-design, lifecycle transparency, and algorithmic efficiency as foundational principles. While technologies like large language models (LLMs) and deep learning architectures promise gains in sustainability applications, their effective use depends on organizational capabilities to evaluate, absorb, and govern these tools responsibly. This highlights the strategic importance of knowledge-based enablers that ensure alignment between AI deployment and long-term sustainability goals [2]. Some studies also highlight the role of AI to promote Sustainable development goals (SDGs). Leal Filho et al. [20] argue that AI plays a central role in promoting sustainable cities (SDG 11), highlighting applications such as energy management, waste management, traffic optimization, and environmental sustainability. Nonetheless, those authors caution that ethical, inclusive, and privacy-preserving implementation is essential for its effective use.

Complementing these perspectives, Valencia-Arias et al. [21] explore recent trends in the sustainable AI literature and define a dual-scope framework that addresses the environmental, economic, and social dimensions of AI's sustainability.

Based on the literature, Table 1 comprehends a curated keyword lexicon for sustainability to be included in Scopus query.

Table 1. Keyword lexicon for sustainability.

Keyword	Example Use in Literature
Sustainability	Sustainability is increasingly embedded in AI strategies at the organizational level, requiring capabilities that align AI development with environmental and social priorities. Firms need to integrate sustainability goals into their digital innovation capabilities to remain competitive and compliant [22].
Sustainable development goals (SDGs)	Organizational adoption of AI for SDG alignment depends on strategic leadership and institutional capability to apply AI in sectors like clean energy, education, and smart infrastructure [20].
Green Innovation	Green innovation, enabled by AI, is amplified by organizational capabilities such as technological readiness and absorptive capacity. Firms with strong AI and knowledge-sharing cultures show greater performance in sustainable innovation outcomes [23].
Circular Economy	The transition to circular economy models requires AI-driven data capabilities combined with strategic foresight and organizational learning, allowing firms to optimize reuse, recycling, and material efficiency [24].
Environmental Sustainability	Achieving environmental sustainability through AI involves internal capabilities for cross-functional integration, energy analytics, and dynamic resource allocation—enabled by AI systems trained on sustainable objectives [25].
Environmental Governance	AI supports environmental governance when embedded within organizational routines that emphasize transparency, auditability, and stakeholder accountability. Capabilities in responsible data use, ethical oversight, and real-time monitoring are essential for aligning AI with governance goals [26].

Green AI	Green AI, which prioritizes energy-efficient and environmentally aware AI development, is enabled by organizational capabilities in sustainable computing infrastructure, carbon-conscious design, and internal R&D governance [24].
Responsible AI	The operationalization of responsible AI depends on capabilities for ethical governance, stakeholder engagement, and cross-functional alignment. Organizations must cultivate cultural and procedural mechanisms to ensure that AI innovation contributes to sustainability and social equity [26].
Energy Optimization	AI-driven energy optimization requires firms to develop capabilities in real-time analytics, demand forecasting, and digital infrastructure integration. These are critical for improving energy efficiency in operations and reducing organizational carbon footprints [27].
Net Zero	Achieving net-zero emissions through AI requires strategic capabilities in emissions accounting, cross-sectoral AI integration, and long-term innovation alignment. Firms that invest in these capabilities can leverage AI to support sustainable industrial transitions [28].
Renewable Energy	In the context of renewable energy deployment, AI capabilities such as intelligent forecasting, system learning, and adaptive optimization must be supported by organizational digital maturity and cross-sector collaboration [27].

The growing integration between innovation and AI has driven the development of conceptual frameworks that aim to organize key terms, concepts, and practices emerging from this interdisciplinary field. The use of a structured lexicon of innovation and AI not only facilitates communication among researchers and professionals, but also enables more precise analysis of trends, patterns, and impacts of these technologies across domains. Recent studies have applied bibliometric and semantic approaches to map keywords, thematic categories, and relationships among core concepts such as data-driven innovation, AI-powered entrepreneurship, ethical regulation, open innovation, and machine learning [29].

Moreover, the practical application of keyword extraction techniques, such as in the study by Wang [30], associates the use of AI technologies with indicators of technological innovation, demonstrating the relevance of lexical analysis in understanding the adoption and impact of these tools in organizations. Petrescu et al. [31] propose a conceptual framework for AI-based innovation in B2B marketing, organizing the lexicon around four analytical dimensions: IT resource environment, innovative actors, marketing knowledge, and communication relationships.

From an ethical and methodological standpoint, Sriram [32] highlights the importance of establishing clear terminologies to discuss the impacts of AI on academic writing, addressing concepts such as academic integrity, AI disclosure, and plagiarism detection, thereby reinforcing the need for a shared normative and interpretive vocabulary.

Recent research underscores the importance of policy-level strategies that integrate AI into educational programs, emphasizing the need for multidimensional approaches and practical recommendations to redesign graduate curricula for fostering sustainability, innovation, and the essential skills required in an increasingly AI-driven future [33].

Finally, the application of a structured lexicon also proves relevant in the educational context. The contemporary AI lexicon now systematically includes the terms AI Agents and Agentic AI, as articulated by Sapkota et al. [34]. These authors provide a detailed conceptual taxonomy distinguishing the two paradigms: AI Agents are modular systems guided by LLMs and designed for goal-directed task execution, whereas Agentic AI represents a paradigm shift involving multi-agent collaboration, persistent memory, and dynamic coordination to accomplish complex objectives [34].

Therefore, the systematic inclusion and use of an innovation and AI lexicon in academic research is not only justified but essential for ensuring conceptual coherence, analytical clarity, and the replicability of studies in this rapidly evolving field. Thus, the lexicon for AI and innovation comprehends the terms included in Table 2.

Table 2. Keyword lexicon for AI and innovation.

Keyword	Example Use in Literature
Artificial Intelligence (AI)	AI is widely acknowledged as a transformative general-purpose technology with significant implications for addressing complex sustainability challenges across environmental, economic, and social dimensions [35].
AI-Driven Innovation	AI-driven innovation encompasses the application of artificial intelligence to accelerate sustainable product, process, and service development through advanced analytics and automation [36].
Machine Learning	Machine learning models enhance sustainability efforts by enabling real-time predictive capabilities in climate risk assessment, energy efficiency, and environmental monitoring [37].
dhimanDeep learning	Deep learning techniques contribute to sustainable innovation by enabling sophisticated data-driven modeling for complex phenomena such as energy optimization and climate simulations [38].
Neural networks	Artificial neural networks are employed for intelligent pattern recognition and predictive analytics in sustainability applications, including emissions forecasting and smart infrastructure design [38].
Big Data analytics	Big data analytics is a critical enabler of AI-based sustainability by facilitating high-volume data processing, enhancing environmental decision-making, and detecting greenwashing in ESG disclosures [39].
Predictive analytics	Predictive analytics supports sustainable strategies by forecasting energy demand, optimizing supply chains, and improving ecological resource allocation through AI-driven insights [40].
Smart systems	Smart systems, powered by AI and IoT, facilitate adaptive infrastructure for sustainability by dynamically managing resources such as energy, water, and waste in real time [41].
Knowledge management	Integrating AI with organizational knowledge management enhances absorptive capacity and amplifies the firm's ability to innovate sustainably and respond to environmental complexity [35].
Digital transformation	Digital transformation encompasses the strategic integration of digital technologies, including AI, to drive sustainable value creation and systemic organizational change [42].
AI capability	AI capability refers to a firm's technological readiness and absorptive competencies to develop, deploy, and scale AI solutions aligned with sustainability objectives [36].
Organizational learning capability	Organizational learning capability serves as a moderator that enables firms to fully leverage AI technologies for enhanced innovation performance in sustainability-oriented contexts [43].
Generative AI (GenAI)	Generative AI offers potential for sustainable innovation through design optimization and simulation, but also poses environmental concerns due to the computational intensity of large-scale models [44].
Large language models (LLM)	LLMs enable scalable natural language processing for sustainability reporting and policy analysis, though concerns persist regarding their energy demands and carbon footprint [44].
Agentic AI & AI agents	Agentic AI refers to autonomous systems capable of goal-directed behavior with minimal human input, increasingly used to enhance sustainability in sectors like energy, logistics, and infrastructure [45].
Computer vision	Computer vision techniques are applied in sustainable domains such as satellite-based environmental surveillance, biodiversity monitoring, and energy-efficient architecture [38].
Natural language processing (NLP)	NLP enables the analysis of sustainability discourse, stakeholder sentiment, and regulatory trends; however, it remains resource-intensive and requires greener AI infrastructure [37].

3. Methodology

This study investigates how AI-driven innovation can be effectively aligned with sustainability strategies by identifying the knowledge-based organizational capabilities that enable this integration. To achieve this, we adopted a mixed-methods approach that combines bibliometric mapping with thematic synthesis, allowing for both quantitative analysis of research trends and qualitative interpretation of conceptual structures. While the bibliometric component reveals the intellectual landscape of the field, the qualitative analysis enables the identification of core capability clusters related to knowledge management (KM), organizational learning, and strategic leadership.

As academic interest in AI and sustainability continues to expand, the volume and diversity of related publications pose challenges to manual review processes, which often result in inconsistency and limited coverage. To ensure rigor and scalability, we employed automated bibliometric tools to uncover patterns, extract thematic clusters, and construct a structured framework of capabilities supporting sustainable AI innovation. The full research design is outlined in Figure 1.

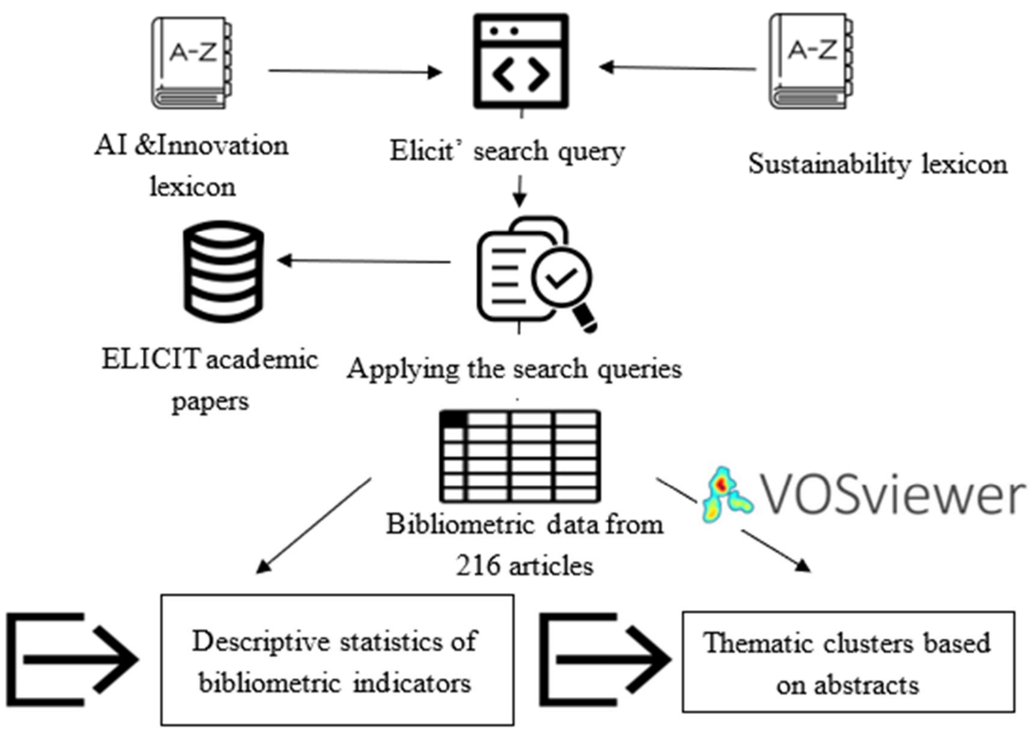

Figure 1. Research strategy—Workflow outlining the steps from identifying articles with Elicit to bibliometric and thematic analysis for synthesizing results.

3.1. Data Collection

To identify and organize relevant literature, we used Elicit, an AI-powered research assistant designed to streamline evidence synthesis. For open-access articles, Elicit uses the full-text content retrieved from papers; for others, metadata and abstracts are used as the primary sources of information. Elicit significantly enhanced the efficiency and rigor of the review process by automating repetitive screening tasks and facilitating both structured data extraction and synthesis. As a recognized and increasingly adopted AI tool in academic research workflows, Elicit exemplifies how language model–powered systems can streamline evidence collection, accelerate analysis, and support more scalable and reproducible scientific inquiry [46].

Using the lexicon listed in Tables 1 and 2, an Elicit search query can be constructed to retrieve documents that address both AI/innovation and sustainability aspects. The query uses an AND to join the two thematic groups of keywords, and OR within each group to include synonyms and related terms. To ensure the specificity and thematic accuracy of the dataset, a deliberate strategy was adopted regarding the inclusion of acronyms and full terms. Acronyms with high semantic ambiguity, such as "NLP" (Natural Language Processing) and "ML" (Machine Learning), were excluded from the query in their abbreviated form to avoid retrieving documents from unrelated fields (e.g., "Neuro-Linguistic Programming" or "Maximum Likelihood"). Instead, we used the full terms to improve precision. Conversely, acronyms with high disciplinary specificity and established use, such as "LLMs" (Large Language Models), were included alongside their full counterparts, as their usage is semantically consistent within the AI literature. This decision balances completeness with topical relevance and aligns with best practices in bibliometric keyword design. The full query is presented:

("artificial intelligence" OR AI OR "AI-driven innovation" OR "responsible AI" OR "green AI" OR "machine learning" OR "deep learning" OR "neural network" OR "predictive analytics" OR "smart systems" OR "knowledge management" OR "digital transformation" OR "AI capability" OR "big data analytics" OR "generative AI" OR "large language models" OR "LLMs" OR "agentic AI" OR "AI agent*" OR "computer vision" OR "natural language processing")*

AND

(sustainab OR "sustainable development" OR "Sustainable Development Goals" OR SDGs OR "green innovation" OR "circular economy" OR "environmental sustainability" OR "environmental governance" OR "net zero" OR "renewable energy")*

A total of 216 peer-reviewed articles were systematically selected and reviewed, with the sample restricted to publications in Q1-ranked journals to ensure a high standard of scholarly quality and academic rigor, given the well-documented advantages of Q1 journals in terms of citation impact, research excellence, and visibility, as emphasized in bibliometric studies [47]. The analysis focused on core elements extracted via Elicit: main findings and discussion presented by the authors.

3.2. Text Mining and Co-Word Analysis

This study applies text mining techniques to extract latent structures and thematic patterns embedded within the document corpus. As outlined by Calheiros et al. [48] text mining facilitates the detection of recurring concepts through the analysis of word frequency and co-occurrence. To ensure analytical relevance, preprocessing steps such as stemming and stop word removal were implemented. Stemming reduces words to their morphological root (e.g., "learning" becomes "learn"), thereby grouping semantically related terms. Stop word removal excludes generic or contextually redundant terms—such as “paper”, “study”, or frequently occurring domain-specific phrases like “artificial intelligence” or “AI—to mitigate noise and enhance the clarity of the extracted themes.

The refined corpus formed the basis for a co-word analysis, a technique that identifies semantic linkages between terms by examining their co-occurrence within the same document, and organizes them into clusters to reveal conceptual structures. This analysis was conducted using VOSviewer version 1.6.20 (released October 2023), which incorporates recent algorithmic refinements while maintaining methodological principles detailed by Eck and Waltman [49]. Several software tools are available for bibliometric and thematic analysis, including Bibliometrix, CiteSpace, and SciMAT, each with distinct strengths in data processing, visualization, and topic evolution mapping. In this study, we selected VOSviewer because it offers robust algorithms for co-occurrence analysis and network visualization, is widely adopted in the literature for mapping conceptual structures, and allows for parameter fine-tuning (e.g., occurrence thresholds, relevance scores) that aligns with our research objectives [50]. Alternative techniques such as Latent Dirichlet Allocation (LDA) or BERTopic offer probabilistic and transformer-based topic modeling, respectively [51]. However, these models identify abstract topics rather than relational term networks. Since our objective was to map conceptual structures linked to capability domains, VOSviewer’s co-occurrence clustering was considered more appropriate. While future studies could benefit from triangulating these approaches, the present analysis achieved sufficient granularity and interpretive clarity through VOSviewer alone.

3.3. Thematic Cluster Identification

VOSviewer employs natural language processing techniques—specifically leveraging the Apache OpenNLP library—to construct network visualizations that map the co-occurrence relationships among terms within the corpus. These network maps reveal clusters of frequently co-occurring words, each representing a distinct thematic domain within the broader research field. As highlighted by Eck and Waltman [49], this method provides a more refined perspective on the structure of scientific literature compared to traditional clustering approaches, capturing the complexity and interconnectedness of topics.

In this study, we considered terms with a minimum frequency of seven occurrences within the corpus. This threshold was selected to ensure the inclusion of conceptually meaningful but potentially less frequent terms, particularly given that the corpus was derived from the distilled content of each article, i.e., the main findings and author discussions. Since these sections are inherently more concise than full texts, a lower frequency threshold allowed for a more representative capture of relevant vocabulary without compromising analytical validity.

To further focus the analysis on the most significant terms, we restricted the co-occurrence mapping to the top 60% of terms ranked by relevance. This threshold follows the default configuration and practical recommendations by the VOSviewer developers, who suggest that selecting approximately 60% of noun phrases typically yields a meaningful balance between relevance and coverage [52]. This empirical approach helps to filter out overly generic terms while retaining the most informative ones for the field under study. This filtering strategy ensured that the resulting network emphasized the most salient linguistic patterns while maintaining a comprehensive view of the thematic landscape.

4. Results and Critical Analysis

4.1. Insights from Bibliometric Analyses

The bibliometric analysis provides additional insights into the temporal evolution and authorship patterns of the 216 articles included in the dataset, covering the period from 2017 to early 2025.

The volume of publications in the field has grown steadily since 2017. The earliest records in the dataset date from 2017 and 2018, with only one publication each year. A first notable increase occurred in 2020, when output rose to 25 articles, followed by a continued upward trajectory. The year 2024 marked the highest number of publications, with 62 articles, representing a nearly 24-fold increase compared to 2017. The dataset also includes 10 articles published in the first months of 2025, indicating that scholarly interest remains strong.

The analysis of source titles reveals that a limited number of journals concentrate a significant portion of the publications. Specifically, seven journals account for more than three articles each, together representing 100 of the 216 papers included in the dataset. The journal Sustainability leads with 63 publications, followed by the Journal of Cleaner Production (9 articles), Sustainable Development (8 articles), and Business Strategy and the Environment (7 articles). Other relevant outlets are Technological Forecasting and Social Change (5 articles), Heliyon (4 articles), and Energies (4 articles). This concentration indicates that almost half of the research in the field is published in a small group of interdisciplinary and sustainability-oriented journals, underscoring their role as central venues for debates on AI, innovation, and sustainability.

The analysis shows that most publications were the result of collaborative research. Out of the 216 articles, 183 (84.7%) were multi-authored, while only 33 (15.3%) were written by a single author. Collaboration has been the dominant pattern across all years, with its prevalence increasing over time. For instance, in 2020, single-authored articles represented 44% of publications, whereas in 2023 and 2024, they accounted for less than 10%.

The temporal distribution of authorship patterns reveals a shift towards larger research teams in recent years. This suggests that collaboration has become an increasingly important strategy for producing impactful work in the domain of AI-driven innovation and sustainability. The sustained dominance of multi-authored papers aligns with broader trends in interdisciplinary research, where complex topics often require diverse expertise.

When considering citation impact, five journals stand out with more than 500 citations each within the analyzed dataset. Sustainability is the most cited outlet, with a total of 3271 citations, confirming its prominence as both the most productive and most influential journal in this field. Nature Communications follows with 1674 citations, despite having fewer articles in the dataset, reflecting the high visibility and citation impact of this multidisciplinary journal. The Journal of Cleaner Production (1071 citations), Business Strategy and the Environment (836 citations), and Technological Forecasting and Social Change (787 citations) also show strong influence, underscoring the relevance of sustainability, environmental management, and foresight studies in shaping the research agenda at the intersection of AI and innovation for sustainability. Together, these journals demonstrate that impact is not only concentrated in specialized sustainability outlets but also spans highly ranked interdisciplinary platforms.

4.2. Thematic Clusters

The five thematic clusters identified form the conceptual foundation of a capability-based framework for aligning AI-driven innovation with sustainability strategies. Each cluster reflects a distinct yet interrelated set of organizational capabilities, offering insight into how firms operationalize knowledge, leadership, governance, and collaboration in sustainable digital transformation (Figure 2).

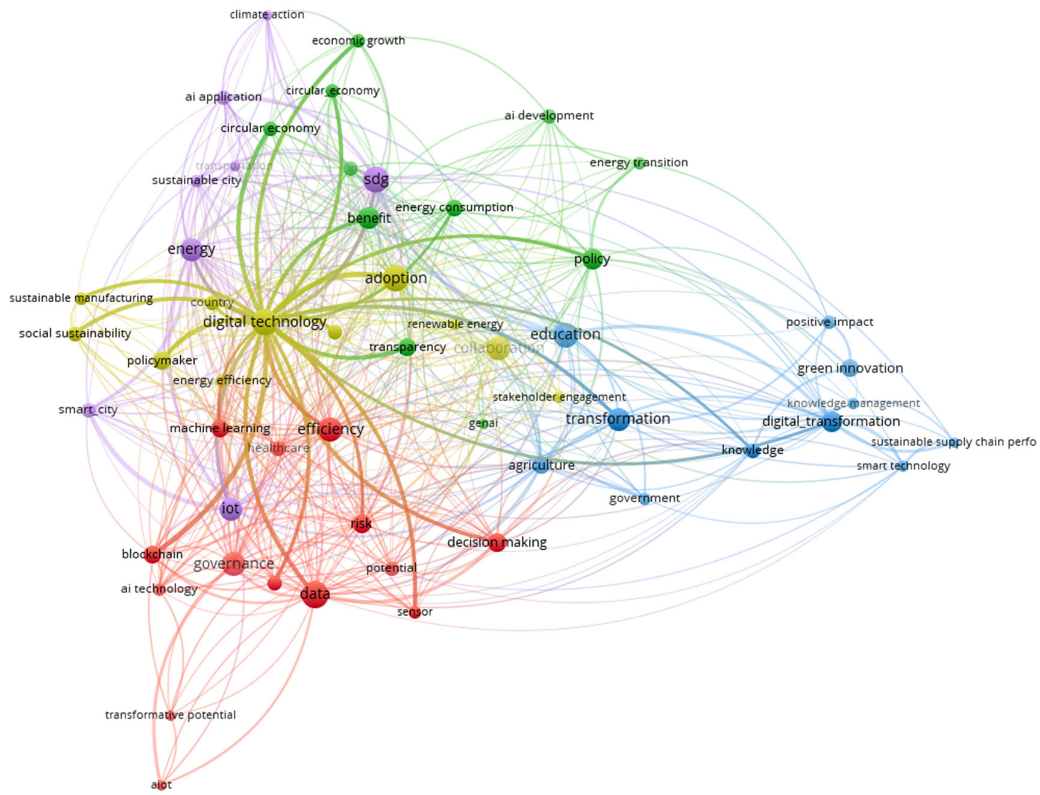

Figure 2. VOSviewer network visualization of ten thematic clusters in AI-driven environmental research.

To support the interpretation of the thematic clusters identified through the co-occurrence analysis, a detailed characterization of each cluster was conducted based on the most frequent terms. Table 3 presents the key terms associated with each thematic cluster, along with their frequency of occurrence in the dataset. This allows for a clearer understanding of the conceptual focus of each cluster.

Table 3. Clusters' characterisation.

Cluster	Most Frequent Terms	Number of Occurrences
1—Data governance and decision intelligence (in red)	data	37
	governance	33
	efficiency	27
	decision making	17
	risk	16
	healthcare	15
	blockchain	15
	machine learning	14
	potential	12
	environmental impact	10
2—Policy-driven innovation and green transitions (in green)	benefit	23
	policy	20
	transparency	14
	ai development	13

	energy consumption	13
	ai model	12
	energy transition	9
	circular economy	9
3—Digital transformation through education and innovation (in blue)	education	37
	transformation	26
	digital transformation	21
	green innovation	19
	agriculture	18
	positive impact	11
	government	10
4—Collaborative adoption for sustainable outcomes (in yellow)	adoption	33
	digital technology	33
	collaboration	32
	policymaker	15
	energy efficiency	11
	country	10
	social sustainability	10
5—AI for smart cities and climate action (in purple)	SDG	33
	IoT	26
	energy	25
	smart city	13
	ai application	12
	sustainable city	10
	transportation	7
	climate action	7

The first cluster, in red, ("Data governance and decision intelligence") centers on data management, decision-making efficiency, and risk governance. This cluster emphasizes the critical role of organizational capabilities related to data management, operational efficiency, and informed decision-making in sustainability-oriented AI strategies. The five most frequently occurring terms—data, governance, efficiency, decision making, and risk—collectively unveiling a narrative: that aligning AI innovation with sustainability depends not only on technological tools but also on the institutional capacity to manage and govern information effectively. This is consistent with the knowledge-based view, which emphasizes that dynamic capabilities such as knowledge integration and strategic sensing are essential for navigating uncertainty and supporting data-driven strategic alignment [53].

Indeed, the prominence of terms like data and governance within this cluster underscores the critical need for robust institutional structures capable of ensuring ethical data use, regulatory compliance, and transparency—core principles for sustaining trust in AI systems. This interpretation is reinforced by academics [54], which highlights how evolving data governance frameworks are essential for embedding AI into sustainability policy, particularly through mechanisms that promote accountability and institutional oversight.

Closely related are the terms efficiency and decision-making, which reflect the increasing use of AI to optimize organizational performance and responsiveness. For example, Fan et al. [55] provide evidence of how AI and deep learning contribute to system-wide efficiency and proactive risk mitigation, notably in areas such as healthcare and environmental monitoring. These applications are enabled by integrated data infrastructures and algorithmic decision-support systems that simultaneously enhance performance and ethical stewardship. This dual benefit has also been highlighted in literature on AI-enabled decision intelligence, where performance optimization is linked with increased agility and sustainability metrics [56].

Moreover, the inclusion of risk in this cluster signals a growing emphasis on resilience-oriented planning and predictive analytics within sustainability contexts. Raman et al. [57] illustrates this dynamic in the renewable energy sector, where real-time data flows and AI-driven decision-making are essential to support adaptive learning and long-term transitions. Together, these studies affirm the centrality of data governance, algorithmic efficiency, and risk-awareness as interdependent enablers of sustainable AI deployment.

The second cluster in green, referred to as Policy-driven innovation and green transitions, underscores the strategic role of regulatory frameworks, technological development, and environmental policy in shaping the application of AI for sustainability. The five most frequently occurring terms in this cluster—benefit, policy, transparency, AI development, and energy consumption—reveal a strong orientation toward institutional structures and macro-level enablers that influence how organizations leverage AI to support sustainable transitions.

The emphasis on policy and transparency in this cluster highlights that organizational alignment with sustainability goals is deeply embedded in broader governance structures and public accountability. Rather than occurring in isolation, sustainable AI implementation depends on transparent, inclusive policy-making processes that define the boundaries and incentives for innovation. Empirical evidence supports this argument, showing that transparency mechanisms and AI policy co-design with stakeholders significantly improve both ethical compliance and long-term legitimacy of digital transitions [58].

This is clearly articulated by Kulkov et al. [54], which review how regulatory frameworks shape AI development for sustainability, particularly in high-impact sectors like energy and transportation, where AI can serve as both an enabler and a risk.

Terms such as AI development and energy consumption point to growing awareness of the environmental costs associated with digital technologies. Studies [59] responds to this concern by proposing the concept of Green AI, which advocates for the design of models that minimize energy use and computational demand. The study emphasizes that embedding energy efficiency at the design stage requires not only technical innovations but also strong policy support and cross-sectoral coordination. These efforts are especially urgent given rising critiques of AI's environmental footprint, with calls for Green AI paradigms that integrate carbon accounting into AI model development and lifecycle evaluation [60].

Meanwhile, the presence of the term benefit signals a shift toward pragmatic, outcome-oriented thinking—where the integration of AI must deliver measurable economic, environmental, or social gains. This logic is well illustrated in literature [61], which examines the interplay between circular economy strategies and AI deployment. The paper shows how regulatory instruments and public incentives can unlock AI's potential to generate concrete sustainability benefits across complex industrial value chains. Together, these studies underscore how AI's contribution to sustainability is contingent on robust policy frameworks, environmental awareness, and a results-driven mindset.

The third cluster in blue, designated "Digital transformation through education and innovation", focuses on the enabling role of education, digital literacy, and green innovation in promoting sustainability, particularly in sectors such as agriculture and supply chains. The five most frequent terms in this cluster—education, transformation, digital transformation, green innovation, and agriculture—reveal how knowledge-oriented and sector-driven capabilities serve as fundamental levers for organizational alignment between AI and sustainable development goals. The prominence of education and digital transformation within this cluster suggests that sustainable AI strategies extend beyond technical capacity—they require deep institutional and cultural commitments to continuous learning and capability development. This view is supported by academics [62] which emphasize that AI's societal benefits—such as raising environmental awareness or fostering responsible digital behavior—depend heavily on inclusive educational reforms and inter-sectoral knowledge exchange. In particular, those authors highlight that sustainability literacy and critical thinking must be embedded in education systems to guide ethical engagement with AI technologies. This aligns with theories of organizational learning that position education as a strategic lever for digital innovation and sustainability-oriented adaptation.

In applied contexts like agriculture, the role of digital capability becomes even more apparent. Studies [63] demonstrates that while AI offers pathways for greener farming practices, its success is contingent on the institutional learning required to support local adoption. Likewise, Mana et al. [63] find that AI-driven innovation in rural development is most effective when accompanied by targeted educational programs that address structural barriers such as skill shortages and limited access to technology.

The cluster also reveals the importance of green innovation, reflecting the need for organizations to align digital transformation with environmental performance. Guandalini [64] supports this perspective by identifying education, innovation readiness, and leadership as foundational elements in public and private sector efforts to integrate AI into sustainability transitions.

Finally, the concept of transformation captures the broader systemic shifts—technological, social, and organizational—necessary to embed AI into long-term sustainability strategies. As these studies show, institutions that invest in human capital, promote digital literacy, and build innovation ecosystems are better equipped to drive the socio-technical change that sustainable AI implementation demands.

The fourth cluster in yellow, "Collaborative adoption for sustainable outcomes", emphasizes multi-stakeholder collaboration, technology adoption, and policymaker engagement as key drivers of sustainability. The five most frequent terms—adoption, digital technology, collaboration, policymaker, and energy efficiency—reflect a multidimensional understanding of how organizational and cross-organizational capabilities enable the successful deployment of AI in sustainability-oriented contexts. The prominence of adoption and digital technology in this cluster highlights the pivotal role of absorptive capacity and digital readiness as prerequisites for effective AI deployment. These organizational capabilities determine the extent to which new technologies can be internalized, contextualized, and scaled. Nti et al. [65] emphasize that successful digital adoption in urban systems relies not only on infrastructure but also on participatory governance and collaborative innovation ecosystems—factors that enable organizations to adapt AI solutions to complex local realities. Such collaborative approaches are reflected in smart governance models, where co-creation among actors leads to more resilient and context-sensitive AI deployments [66].

This perspective is deepened by the recurring presence of collaboration and policymaker, which reflects the inherently relational nature of sustainability transitions. Rather than emerging in isolation, AI innovations are shaped by coordinated efforts across governments, businesses, and civil society. Vinuesa et al. [67] exemplify this by showing that realizing AI's potential across 134 SDG targets hinges on strategic alliances between policymakers, researchers, and industry actors. Similarly, studies [20] underscore that regulatory coherence and shared long-term visions between developers and policy actors are essential to scaling AI in domains such as energy, mobility, and infrastructure.

The inclusion of energy efficiency further grounds this cluster in measurable operational outcomes. Nti et al. [65] illustrate that gains in energy performance are maximized when AI implementation is co-designed and continuously monitored by multiple stakeholders. Blasi et al. [68] reinforce this operational logic, showing that successful AI uptake in low-carbon manufacturing depends on public–private co-investment and collaborative governance structures.

Moreover, Bibri et al. [69] highlight how collaboration in circular economy initiatives, supported by shared data ecosystems, enhances both adoption rates and equity in sustainability outcomes. Collectively, these findings suggest that AI-driven sustainability is not just about technology—it is about building the institutional conditions for shared ownership, responsive policy alignment, and multi-actor value creation. This cluster thus foregrounds a capability set rooted in strategic collaboration, institutional coordination, and inclusive governance as enablers of responsible and impactful AI adoption.

Finally, the fifth cluster, AI for smart cities and climate action, explores how AI applications—particularly in combination with Internet of Things (IoT)—are shaping sustainable urban development, energy management, and climate-related interventions. The five most frequent terms—SDG, IoT, energy, smart city, and AI application—highlight the growing role of AI in transforming infrastructure, urban governance, and environmental monitoring systems in pursuit of the SDGs. The prominence of SDG and smart city in this cluster reflects a globalized sustainability orientation, where AI is not merely a technical tool but a strategic enabler of long-term transformation at urban and regional levels. This interpretation aligns with previous studies [67], which maps AI's potential contribution to 134 sustainability targets across the SDG framework—many of which are embedded in urban infrastructure, transport, and energy systems. The study positions AI as a foundational digital infrastructure layer capable of responding to complex sustainability challenges with data-driven precision.

The frequent co-occurrence of IoT and AI application points to the technological convergence driving modern urban systems. Studies [70] provide empirical grounding for this by showing how real-time data from interconnected devices enhances urban responsiveness—optimizing traffic flow, improving resilience, and reducing emissions in smart city initiatives. However, the authors also stress that these technological benefits are fully realized only when supported by institutional capacity and community engagement, reinforcing the importance of inclusive governance.

The presence of the term energy brings attention to AI's dual role in optimizing consumption and managing renewable energy sources. Academics [71] demonstrate how AI-enabled energy management systems in buildings and utilities can predict demand, detect inefficiencies, and significantly reduce energy waste and carbon output. Complementing this, Singh et al. [72] examine AI's role in urban mobility, emphasizing how intelligent transport systems support low-carbon transitions by improving accessibility and reducing emissions across dense urban corridors. This reflects a broader movement toward AI-augmented smart infrastructures where energy management systems serve as critical instruments for operational decarbonization [73].

Finally, Nahar [74] contributes a governance perspective by advocating for inclusive, equitable AI design in smart cities. The study underscores that technological integration must be paired with frameworks that ensure broad participation and climate justice, particularly in vulnerable communities.

Altogether, this cluster identifies a capability set centered on urban digital infrastructure, technological integration, and adaptive governance. Cities and organizations that excel in deploying AI within smart city frameworks are those that combine real-time decision-making with institutional coordination and alignment with global sustainability goals—positioning themselves as leaders in digitally enabled, climate-resilient transformation.

Taken together, these five thematic clusters form a capability-based framework that captures how organizational knowledge, leadership, collaboration, and governance interact to support sustainable AI innovation.

4.3. Capability-Based Framework and Strategic Implications

Building on the thematic clusters identified through co-occurrence analysis, this section synthesizes the conceptual insights into a capability-based framework that explains how organizations can align AI-driven innovation with sustainability-oriented strategies. While the preceding analysis mapped the intellectual landscape of the field, this section translates these findings into a more actionable structure by categorizing key organizational capabilities and connecting them to strategic roles, themes, and practical implications.

Table 4 presents a synthesized overview of the five capability domains identified, each representing a distinct cluster of organizational competencies that underpin the integration of AI and sustainability. The mapping between clusters and capability domains was conducted through qualitative interpretation of the terms and thematic content of each cluster. This interpretive analysis was grounded in the theoretical framework of organizational capabilities and aimed to synthesize how the identified themes align with distinct capability areas discussed in the literature. These domains are not mutually exclusive; rather, they form a mutually reinforcing system of capabilities. For instance, capabilities in data governance are complemented by those in collaborative innovation or policy alignment, enabling a holistic and adaptive approach to digital sustainability transformation.

The table also links each domain to its dominant capabilities (e.g., knowledge integration, absorptive capacity, strategic leadership), core strategic functions (e.g., risk mitigation, legitimacy building, policy responsiveness), and recurring thematic foci (e.g., education, smart cities, green transitions). This categorization helps clarify how different types of capabilities contribute to innovation outcomes that are both technologically advanced and sustainability-aligned.

Table 4. Capability domains and their strategic implications for sustainable AI innovation.

Capability Domain	Main Thematic Clusters	Key Capabilities	Organizational Level	Illustrative Application
Knowledge and learning capabilities	1 (Data governance), #3 (Education & innovation)	Knowledge integration, Organizational learning, Absorptive capacity, Sustainability literacy	Individual & Organizational	Internal AI training for sustainable agriculture or circular economy
Governance and ethical infrastructure	1 (Data governance), 2 (Policy & Green AI)	Data governance, Risk management, Transparent decision-making, Ethical oversight		Green AI models with carbon accounting and explainable algorithms
Collaborative and institutional capabilities	2 (Policy & Green AI), #4 (Collaboration)	Multi-stakeholder engagement, Policy co-creation, Public–private partnerships	Ecosystem & Inter-organizational	SDG-aligned AI projects across academia, government, and industry
Technological Integration capabilities	4 (Adoption), 5 (Smart cities)	Smart infrastructure, Digital transformation, AI-enabled energy efficiency, IoT convergence	Operational & Technical	AI-powered smart grid in urban mobility or emission reduction

Taken together, these capability domains suggest that sustainable AI innovation is not driven solely by technical infrastructure or algorithmic sophistication, but by the dynamic orchestration of knowledge-based, strategic, and relational competencies. These capabilities enable organizations to engage with uncertainty, align technological innovation with institutional logics, and embed sustainability principles into everyday decision-making.

Importantly, the findings imply that capability-building should be seen as a multi-level endeavor—requiring investment not only in digital infrastructure, but also in education, leadership development, policy alignment, and inter-organizational collaboration. Organizations must thus shift from isolated technological experimentation to systemic innovation models grounded in absorptive capacity, strategic foresight, and collaborative governance.

This integrative framework offers a conceptual bridge between the bibliometric findings and practical recommendations, helping both scholars and practitioners to better understand where, how, and why specific organizational capabilities matter in the pursuit of sustainable, AI-enabled innovation.

5. Practical and Policy Recommendations

This section translates the capability-based framework into a roadmap of practical and policy recommendations. Rather than remaining at the conceptual level, the roadmap organizes the findings into concrete steps that organizations and ecosystems can follow to guide the responsible and sustainability-oriented adoption of AI.

5.1. Practical Recommendations for Organizations and Ecosystems

The capability-based clusters identified in this study yield critical insights into how organizations can pragmatically align AI deployment with sustainability objectives. Beyond technological investment, firms must develop human, relational, and institutional capabilities that support ethical, adaptive, and collaborative innovation.

For instance, Cluster 1 highlights the strategic importance of robust data governance, risk-informed decision-making, and ethical AI deployment. These capabilities are essential for high-stakes sectors such as healthcare, energy, and logistics, where both operational performance and reputational risk are tightly coupled with data integrity and algorithmic transparency.

Cluster 2 illustrates that policy literacy, regulatory foresight, and institutional transparency are necessary conditions for sustainable AI development. Organizations must not only comply with existing frameworks but also co-evolve with them. This calls for public–private co-creation mechanisms and adaptive regulatory models that balance innovation with social accountability.

Cluster 3 emphasizes the role of organizational learning and multi-actor innovation ecosystems. Universities, professional training institutions, and employers must collaborate to foster AI readiness, sustainability literacy, and green innovation. This is especially relevant in sectors like agriculture, supply chains, and public services, where AI can unlock sustainability gains but also risks reinforcing existing inequalities if skills gaps persist.

Cluster 4 shows that strategic collaboration and stakeholder alignment are key enablers of sustainable AI adoption. Institutions must cultivate the relational capacity to operate within complex innovation ecosystems, establishing trust-based partnerships across sectors and governance levels. Co-creation and participatory design processes emerge as necessary conditions for context-aware deployment.

Finally, Cluster 5 calls attention to the infrastructure-level capabilities required for AI integration in smart cities, climate action, and energy management. This includes not only technological integration (e.g., IoT, real-time data) but also cross-departmental coordination, real-time monitoring, and alignment with global SDGs.

To support systemic transformation, a cycle of capability-building interventions is proposed, emphasizing both organizational and ecosystem-level action (Figure 3).

Figure 3. Strategic interventions for AI integration in sustainability transitions.

First, governments should launch challenge grants that prioritize AI projects with measurable climate impact, particularly in sectors like energy, transport, and agriculture. These funding schemes can incentivize responsible AI development and accelerate sustainability transitions. Second, it is essential to upskill the workforce by enhancing digital and sustainability-related competencies. This involves expanding access to training in green AI, data governance, and ethical technology use—especially through micro-credentials and voucher-based programs delivered in partnership with universities and professional bodies.

Third, organizations should establish living labs within academic institutions and local innovation ecosystems. These collaborative spaces facilitate joint experimentation among students, researchers, public agencies, and companies, enabling real-time learning and feedback in AI deployment for sustainability. Fourth, AI literacy programs should be implemented at the community level to build awareness and engagement around AI applications. These initiatives must focus on accessibility and relevance, targeting educators, public servants, and underserved communities, and promoting responsible use of AI in daily life. Fifth, digital audits should be conducted to help SMEs assess their digital maturity and identify opportunities for resource efficiency through AI. These audits can be coordinated through national services and delivered with the support of students and regional innovation agencies.

Sixth, AI testbeds must be developed to provide safe environments for experimentation in high-impact sectors. These controlled spaces allow for the testing of AI models in real-world conditions, supporting regulatory innovation, public–private data sharing, and sectoral adaptation. Finally, it is crucial to integrate AI criteria into public procurement frameworks, ensuring that climate-aligned, transparent, and energy-efficient AI systems are prioritized in government contracts—particularly in areas such as infrastructure, mobility, and urban planning.

5.2. Policy Recommendations for Sustainable AI Innovation

The findings of this study carry significant implications for the design and governance of national and international policy frameworks aimed at aligning AI with sustainability transitions. The evidence suggests that AI should not be treated merely as a technological domain requiring digital regulation, but as a systemic enabler of cross-sectoral transformation—implicating environmental, educational, and economic dimensions (Table 5).

Table 5. Policy implications and strategic actions by thematic cluster.

Thematic Cluster	Policy Recommendation	Recommended Strategic Actions
1. Data governance and decision intelligence	Need for ethical data policies, risk management, and AI accountability frameworks.	Develop national data governance guidelines; enforce algorithmic transparency; embed risk metrics in AI evaluation.
2. Policy-driven innovation and green transitions	AI policy must be integrated with sustainability goals and energy efficiency mandates.	Create anticipatory policy sandboxes; align Green AI principles with regulatory instruments; incentivize circular AI.
3. Education and digital transformation	Requires education reform and upskilling to build AI readiness and sustainability literacy.	Launch micro-credential programs in green AI; invest in educator training; embed AI ethics in STEM curricula.
4. Collaborative adoption and multi-stakeholder engagement	Necessitates cross-sectoral governance, co-creation, and participatory policymaking.	Establish regional AI innovation hubs; fund public–private partnership models; promote collaborative policymaking labs.
5. Smart cities and climate action	AI should be embedded into urban planning and climate adaptation policies.	Develop smart infrastructure frameworks; integrate AI into SDG-aligned urban policies; incentivize climate–AI integration.

First, the cross-cluster capabilities identified in this study highlight the necessity of integrated policy approaches that bridge traditional silos between digital innovation, sustainability strategy, and industrial policy. As AI becomes more embedded in core societal systems—such as energy, mobility, agriculture, and education—policymakers must develop governance structures that support multi-domain coordination and long-term mission orientation. This means moving beyond reactive regulation toward anticipatory governance models that align innovation incentives with measurable sustainability outcomes.

Second, the results emphasize the importance of regulatory foresight and dynamic institutional learning. Governments and multilateral organizations must create conditions for adaptive governance that evolves in parallel with technological innovation. This requires a strategic mix of regulatory experimentation (e.g., AI sandboxes, sectoral testbeds), targeted public investment (e.g., green AI challenge grants), and capacity-building mechanisms (e.g., national digital academies, AI literacy campaigns) that foster distributed learning without stifling responsible risk-taking.

Third, this study reinforces the argument that sustainable AI innovation is fundamentally a capability-building endeavor. Rather than relying solely on technological diffusion, effective policy should target the development of complementary capabilities—including data governance, ethical oversight, absorptive capacity, and collaborative infrastructure. These capabilities are necessary to embed sustainability principles into both public administration and industrial ecosystems. In particular, policy should focus on equipping SMEs, municipalities, and educational institutions with the tools and knowledge to co-create, adopt, and govern AI solutions that are inclusive, transparent, and climate-aligned.

Finally, the findings call for distributed, multi-level governance models capable of supporting place-based experimentation and transnational coordination. National governments, regional authorities, universities, and civil society organizations must work together to co-design AI solutions tailored to local sustainability challenges while contributing to global climate and development goals. This includes fostering institutional trust, enabling citizen participation, and ensuring that AI systems deployed in the public interest meet standards of transparency, fairness, and environmental responsibility.

6. Summary of Main Findings

This study systematically examined how knowledge-based organizational capabilities support the alignment of AI with sustainability strategies. Based on the bibliometric and thematic analysis of 216 peer-reviewed articles, the findings reveal five dominant clusters that represent distinct yet interconnected capability domains.

Cluster 1 reveals that organizational capabilities in data governance, decision intelligence, and risk-based thinking form a foundational layer in the alignment of AI-driven innovation with sustainability strategies. These capabilities not only enhance operational performance but also contribute to the resilience and legitimacy of AI applications within complex socio-environmental systems. Similar emphases on responsible data governance and efficiency have been observed in recent reviews that highlight the role of data-centric AI applications in sustainability contexts (e.g., [54,55]).

Cluster 2 reflects a set of organizational capabilities focused on regulatory responsiveness, ethical innovation, and sustainability foresight. This resonates with bibliometric analyses emphasizing the importance of aligning technological trajectories with evolving policy frameworks and sustainability mandates (e.g., [17,20]). Institutions that can interpret and adapt to policy environments, engage in transparent reporting, and align their technological development cycles with sustainability imperatives are therefore better positioned to deliver socially legitimate and environmentally responsible AI-driven innovations.

Cluster 3 emphasizes the enabling role of learning, innovation ecosystems, and sector-specific digital capacities in aligning AI with sustainability. This finding is consistent with studies highlighting the role of digital transformation and organizational learning as key enablers of sustainable practices across industries (e.g., [36,64]). Cluster 4 highlights the pivotal role of stakeholder coordination, technological adoption, and policy engagement in driving sustainability through AI. This aligns with previous works on collaboration and multi-stakeholder governance, which show that strong networks and partnerships are essential for translating technological capabilities into sustainable outcomes (e.g., [65–67]).

Finally, Cluster 5 brings together research that focuses on the application of AI technologies—particularly when combined with IoT—in urban environments and climate mitigation strategies. This corresponds to recent studies emphasizing the transformative potential of AI for sustainable cities and climate action (e.g., [67,70,72]).

The bibliometric mapping conducted with VOSviewer provides empirical validation of these clusters, as illustrated in the network visualization (Figure 2). Table 3 further characterizes the most salient terms within each cluster, confirming the presence of recurring thematic domains across the literature. The structured synthesis presented in Table 4 consolidates these results into four overarching capability domains: knowledge and learning capabilities, governance and ethical infrastructure, collaborative and institutional capabilities, and technological integration capabilities. Together, these domains offer a comprehensive framework that connects organizational routines, leadership practices, and institutional contexts to the operationalization of sustainable innovation.

Importantly, the study demonstrates that sustainable adoption of AI is not driven solely by technological sophistication, but by the dynamic orchestration of knowledge-based, relational, and institutional capabilities. The central contribution of this research lies in providing an integrated capability-based framework that both advances theoretical inquiry and offers practical guidance. By translating dispersed insights into a structured model, the study highlights how firms, policymakers, and educators can design strategies that balance innovation with ethical accountability, regulatory alignment, and environmental responsibility.

7. Limitations and Future Research

While these findings offer a compelling foundation, the research also presents several limitations and opportunities for future exploration. As with any research using bibliometric and text mining techniques, this study presents a number of methodological boundaries that should be acknowledged—though they do not compromise the validity of the results. First, while co-word analysis using VOSviewer enables the identification of latent thematic structures, it is inherently dependent on term frequency and co-occurrence patterns. As such, more nuanced or emergent ideas that appear with lower frequency may not be as prominently represented. This is a recognized trade-off in bibliometric research that privileges scope and structure over depth of individual case analysis. Additionally, future research could also integrate alternative text-mining and topic modeling techniques, such as LDA or BERTopic, to complement co-occurrence network analysis. While VOSviewer offers a robust and widely adopted approach for mapping conceptual structures through co-occurrence clustering, LDA and BERTopic apply fundamentally different algorithms to identify latent topics in large corpora. Combining these approaches in future studies could enhance methodological triangulation, validate thematic clusters from multiple analytical perspectives, and potentially uncover additional emerging themes not detected through co-occurrence mapping alone. Additionally, methods such as Term frequency–Inverse document frequency (TF-IDF) could further enhance thematic extraction in future studies. TF-IDF identifies terms that are not just frequent, but also distinctive within individual documents, helping to surface specific concepts that may be diluted in broader co-occurrence patterns. This could be particularly useful for uncovering less prominent yet highly relevant insights that standard co-word techniques might overlook.

Second, the use of AI-powered tools, such as Elicit, to support the literature review process introduces both benefits and constraints. While Elicit streamlined the identification and organization of relevant papers—enhancing consistency and coverage—it relies on metadata and abstracts, which may not fully capture the theoretical richness or practical detail present in full-text documents. Nonetheless, given the large volume of literature and the structured nature of the research design, this approach was appropriate and allowed for scalable, reproducible analysis.

Third, our inclusion criteria prioritized peer-reviewed journal articles published in English and indexed in Q1-ranked journals. This ensured a high level of academic rigor but may have excluded relevant insights from practitioner literature, policy documents, or non-English academic work. Future research could expand this scope to capture a more diverse set of perspectives.

Another limitation relates to the keyword strategy adopted in the construction of the search query. While the exclusion of ambiguous acronyms (e.g., NLP, ML) helped to reduce false positives and improve thematic relevance, it may also have resulted in the omission of relevant studies that use these acronyms in disambiguated contexts. This reflects a broader trade-off in bibliometric data collection between recall and precision. Future research could triangulate different search strategies or use semantic expansion techniques to evaluate the impact of acronym inclusion on dataset coverage.

Finally, the study is cross-sectional by design and does not explore the temporal evolution of capabilities or sectoral variations. Future work could adopt a longitudinal lens to investigate how capability development unfolds over time, particularly in response to regulatory change, technological advancement, or shifts in sustainability priorities.

8. Conclusions

This study investigated how knowledge-based organizational capabilities enable the alignment of artificial intelligence with sustainability strategies. Drawing on a bibliometric and thematic analysis of 216 peer-reviewed articles, the research combined quantitative mapping with qualitative synthesis to identify five capability clusters and integrate them into a structured framework.

The results show that sustainable AI adoption depends not only on technological sophistication but on the interplay of knowledge integration, organizational learning, ethical governance, and collaborative capacity. By consolidating dispersed insights into a coherent capability-based framework, this study makes a distinct theoretical contribution: it clarifies the foundations of sustainable digital transformation and provides a model that can be applied across diverse sectors.

In practice, the framework offers organizations a roadmap for embedding sustainability principles into AI deployment and supports policymakers in designing adaptive governance mechanisms that foster responsible innovation. These contributions reinforce the academic value of this research while enhancing its practical relevance for firms, educators, and public institutions.

In conclusion, advancing sustainable AI innovation requires more than efficiency or technical performance. It demands organizational readiness, institutional alignment, and cross-sector collaboration. By emphasizing these enabling conditions, this study provides both a foundation for further academic inquiry and a set of actionable insights for stakeholders seeking to align artificial intelligence with the goals of sustainable development.

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