



Artificial Intelligence Adoption and Sustainable Business Performance: A Management of Technology Perspective

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ABSTRACT

Artificial Intelligence (AI) is increasingly recognised as a pivotal factor in achieving sustainable business success; however, the evidence remains inconclusive, with some studies indicating weak or even adverse impacts when organisational factors are considered. This conceptual article introduces an integrated framework that explains how, and under which organisational and technological conditions, AI adoption can enhance economic, environmental, and social performance. It underscores the importance of Management of Technology (Mot) as the central process for transforming AI into value, rather than focusing solely on AI adoption. The study reviews peer-reviewed literature from 2016 to 2026, predominantly from 2021 onward, using a structured narrative literature synthesis approach. It combines the TOE (Technology-Organization-Environment) framework, the Resource-Based View (RBV), and Dynamic Capabilities Theory (DCT) within a management-of-technology perspective. The synthesis shows that AI adoption is conceptually distinct from AI implementation, capabilities, utilisation, and related constructs, which the literature often conflates, impairing causal clarity. A conceptual model shows that AI adoption influences sustainable performance through technology management and innovation capabilities, with organisational agility as a boundary condition. The study formulates ten testable hypotheses and provides an initial measurement instrument for subsequent empirical validation. This research contributes by integrating four theoretical perspectives into a cohesive model, emphasising technology management capability as the vital link between AI and sustainability, and offering a practical roadmap for managers to transform AI investments into sustainable value. Unlike prior studies that treat AI as a generic technology or assess performance solely through financial metrics, this article critically examines AI's sustainability trade-offs such as energy consumption, bias, workforce impact, and governance risks- and contends that AI's sustainability benefits are contingent upon specific conditions, rather than being inherently guaranteed.

Keywords: Artificial Intelligence Adoption, Technology Management, Sustainable Business Performance, Dynamic Capabilities, Innovation Capacity, Organizational Agility, Digital Skills, Responsible AI

INTRODUCTION

Artificial intelligence has evolved from a niche experimental tool to a fundamental technology integral to key organisational functions. Its applications now include predictive analytics, natural language processing, computer vision, and, increasingly, generative and autonomous systems capable of multi-step decision-making [2,3]. Data on enterprise adoption support this trend: in the European Union, AI usage among firms rose from around 7.7% in 2021 to about 20% in 2025, with similar growth in OECD countries (Agentic Economy data referenced in recent studies). Alongside this spread, sustainability has become an essential strategic focus, as regulators, investors, and customers require proof of environmental and social impact alongside financial performance [4,31].

The common assumption that simply adopting AI automatically leads to sustained performance improvements is not supported by careful analysis of the evidence. Firm-level studies increasingly show mixed, conditional, or even null and negative effects of AI on performance. For example, recent research on listed Chinese companies

indicates that AI adoption does not correlate with higher gross operational efficiency and may even be linked to lower net operational efficiency after accounting for confounding variables (as noted in recent financial-distress prediction research). Likewise, many organisations are stuck in a "pilot trap," testing isolated AI projects without scaling them to an organisational level that could produce measurable performance benefits. These results suggest that AI adoption alone is necessary but not sufficient for lasting value creation, and the pathways from adoption to outcomes need much more detailed theoretical and empirical investigation than they have received to date.

A related issue is conceptual ambiguity. Many works use terms such as "AI adoption," "AI implementation," "AI capability," "AI utilization," "digital capability," and "technology management capability" interchangeably, even though these concepts refer to distinct phenomena. For example, deciding to acquire a technology differs from the routines required to operate it, which in turn differs from the broader capacity to orchestrate it strategically [5, 6]. This overlap hampers causal reasoning: studies that examine "performance" with respect to "AI" without clarifying which concept they measure cannot distinguish technological determinism, where AI automatically creates value, from organizational contingency, which depends on complementary managerial capabilities.

This article proposes an integrated conceptual framework, rooted in a Management of Technology (MOT) perspective, to explain how AI adoption leads to sustainable business performance through technology management and innovation capabilities, with organizational agility as a key influence. Its main goals are to: (1) clearly distinguish nine related constructs often conflated in the existing literature; (2) integrate the TOE framework, RBV, and Dynamic Capabilities Theory within an MOT approach to explain the drivers of AI adoption and its value-creation mechanisms; (3) develop a conceptual model and test hypotheses linking AI adoption, technology management, innovation, organizational agility, and multidimensional sustainable performance across economic, environmental, and social dimensions; and (4) critically assess AI's sustainability trade-offs, such as energy use, algorithmic bias, workforce displacement, and governance risks, that a purely techno-optimist view may ignore.

The remainder of the article is organised as follows: Section 2 discusses the theoretical background, while Section 3 reviews the literature across eight thematic areas. Section 4 identifies research gaps. Section 5 introduces the conceptual framework and defines key constructs. Section 6 presents the hypotheses. Section 7 explains the review methodology. Section 8 provides a synthesis of the findings. Section 9 emphasises the Management of Technology perspective as the article's unique contribution. Section 10 proposes a measurement tool. Sections 11–17 cover discussion, contributions, implications, limitations, future research directions, and the conclusion.

2. Theoretical Context

No single theory fully explains how adopting AI translates into sustainable performance. The theories outlined below each highlight a distinct stage in the value-creation process. Rather than presenting them in sequence, their integration forms the core theoretical framework of this article.

2.1 Technology–Organization–Environment (TOE) Framework

The TOE framework [1] analyses technology adoption decisions across three contexts: technological (including benefits, compatibility, complexity, and readiness), organizational (such as leadership support, resources, size, and culture), and environmental (covering competition, regulations, government support, and customer demand). It is now the primary model for understanding the reasons and timing of AI adoption [11,12]. Empirical studies identify key factors like relative advantage, compatibility, sustainable human capital, market demand, and government backing in AI adoption among SMEs (see the TOE-based SME study, Section 3). Although TOE explains the drivers of adoption, it provides limited insights into later organizational processes that translate technology into improved performance. RBV and Dynamic Capabilities Theory address this limitation by operationalising it through Management of Technology.

2.2 Resource-Based View (RBV)

RBV [7] asserts that a sustained competitive advantage stems from resources that are valuable, rare, inimitable, and non-substitutable (VRIN). In the context of AI, RBV research has shifted from treating "AI" as a single resource to decomposing it into tangible resources (such as data, algorithms, and computing infrastructure), human resources (including data science and managerial AI expertise), and intangible resources (such as a data-driven culture, interdepartmental coordination, and risk tolerance) [5]. This breakdown is important because it clarifies that AI infrastructure alone is rarely inimitable, cloud AI services and pre-trained models are becoming more commoditized, whereas organizational resources that manage AI (such as proprietary data, workflow integration, and tacit managerial knowledge) are more difficult to imitate and can provide a competitive edge [5, 8]. Consequently, RBV helps identify which resources are crucial, although, similar to TOE, it does not fully address the dynamic managerial processes, such as the selection, combination, and reconfiguration of resources over time, that are covered by Dynamic Capabilities Theory.

2.3 Dynamic Capabilities Theory (DCT)

Dynamic capabilities describe a firm's skill to combine, develop, and adjust internal and external skills to

succeed in fast-changing settings [9]. This skill is carried out through sensing (identifying AI-driven opportunities), seizing (allocating resources and redesigning business models to realise value), and transforming or reconfiguring (reorganising routines, structures, and assets to incorporate AI-driven workflows) [10]. Recent studies explicitly define AI-enabled dynamic capability (AIDC) as a higher-level managerial skill to coordinate AI resources across these steps, setting it apart from basic AI capability, which only reflects resource availability [25]. This distinction is vital: a firm might possess strong AI capability (such as infrastructure, talent, and data) but lack the dynamic ability to recognise where AI adds value, capture that value via business or process changes, and transform routines, which are essential for long-term performance gains. DCT offers the process framework connecting static resources to performance but remains a broad theory of organizational adaptation. It doesn't specify technology-specific practices- like portfolio management, technology integration, or data governance- needed for effective AI management. These detailed practices are addressed within the Management of Technology perspective.

2.4 Management of Technology (MOT) as the Integrating and Central Perspective

Management of Technology (MOT) encompasses planning, directing, controlling, and coordinating the development and use of technological capabilities to meet strategic and operational objectives [6]. [6] describes technology management as a dynamic capability made up of interconnected activities like identification, selection, acquisition, exploitation, protection, and learning, all of which must be continuously refined as technologies and markets change. This article centres on MOT as its primary, integrative perspective for three reasons. First, MOT makes the abstract concept more concrete.

This article integrates four perspectives to explain the process (see Figure 2 and Section 9): TOE factors clarify why and when a firm adopts AI; RBV explains which resources are accumulated; Dynamic Capabilities Theory outlines the sense–seize–transform cycle that turns resources into value; and Management of Technology specifies the managerial structure for technology selection, integration, governance, human skills, and process redesign. This structure activates the adaptive cycle and ensures sustainability. No single theory suffices because each covers a different aspect of the causal chain. Their combined use is essential to prevent the technological determinism often associated with single-theory explanations. Table 1. Theoretical foundations. Source: Summarised from the foundational theories and referenced literature [1,6,7,9,10,31].

Table 1. Theoretical Foundations

Theory	Main Concept	Application to AI Adoption	Application to Sustainability	Limitation
Technology–Organization–Environment (TOE) [1]	Adoption is shaped by technological, organizational, and environmental contexts	Explains relative advantage, compatibility, readiness, top-management support, and competitive and regulatory pressures as antecedents of AI adoption (Polisetty et al., 2024)	Environmental-context factors (regulatory pressure, stakeholder demand) can be reinterpreted as sustainability-adoption drivers	Descriptive of adoption antecedents ; largely silent on post-adoption value-creation mechanisms
Resource-Based View (RBV) [7]	Sustained advantage derives from valuable, rare, inimitable, non-substitutable resources	Disaggregates AI capability into tangible, human, and intangible resources [5]	Highlights data and green-knowledge resources as potential sources of environmental advantage [31]	Static resource logic; underspecifies how resources are reconfigured over time
Dynamic Capabilities Theory (DCT) ([9,10])	Sensing, seizing, and reconfiguring resources under environmental change	Explains AI-enabled dynamic capability as a higher-order orchestration process distinct from AI capability itself	Reconfiguration processes can incorporate green dynamic capabilities to sustain environmental performance [31]	General theory of adaptation; not technology-specific; risk of tautology if capabilities

				are inferred only from outcomes
Management of Technology (MOT) [6]	Planning, integration, governance, and learning around technological capabilities	Specifies concrete practices — selection, acquisition, integration, data governance, process redesign — that convert AI resources into operational routines	Positions responsible-AI governance and technology evaluation as explicit mechanisms for managing sustainability trade-offs	Less parsimonious; requires integration with broader strategy theories to explain competitive outcomes

3. Literature Review

3.1 Evolution of Artificial Intelligence in Business

The progression of AI in organizations has transitioned from rule-based automation to statistical machine learning and deep learning, then to embedded predictive analytics within enterprise systems, and more recently, to generative and agentic AI capable of autonomous, multi-step tasks [2,3]. Initially, automation managed routine, easily scripted tasks, while machine learning and deep learning improved pattern recognition in unstructured data like images, text, and sensor streams. Predictive analytics integrated these capabilities into operational and strategic decisions, and generative AI expanded AI's roles from analysis to autonomous content, coding, and design creation [26]. Agentic AI advances this further by allowing systems to plan, execute, and adapt complex workflows with minimal human intervention [2]. Each stage adds complexity to technology management: automation mainly involved process engineering, while generative and agentic AI necessitate ongoing data governance, oversight, and auditing for autonomous decisions- activities highlighted by MOT [6]. This evolutionary path shows that organizational capabilities to sustain AI-driven value are continually changing, emphasising a need for a dynamic, technology-management-focused approach rather than a static, tech-only view.

3.2 Artificial Intelligence Adoption in Organizations

Research on AI adoption identifies key factors across various areas. Technological aspects include relative advantage, compatibility, complexity, and readiness. Organisational factors involve top management support, resources, absorptive capacity, and firm size. Environmental influences cover competitive pressure, regulations, and government backing. Managerial elements focus on leadership vision and strategic alignment, while human factors relate to employee skills, acceptance, and resistance. Studies in emerging economies show that relative advantage, compatibility, sustainable human capital, market demand, and government support significantly impact AI adoption, with firm size influencing these effects [11]. Data from Pakistani manufacturing SMEs indicates that technological readiness, leadership vision, and competitive pressure encourage adoption, with AI serving as a link between these drivers and firm performance [12]. Most measurement tools evaluate whether AI is adopted or the level of adoption, rather than the organizational routines needed for effective use, a point discussed in Section 5. Table 2. Determinants of AI adoption. Source: Synthesized from AI-adoption and technology-management literature [11,12,23,24,6].

Table 2. Factors Influencing AI Adoption

Dimension	Factors	Supporting Studies	Expected Influence
Technological	Relative advantage, compatibility, complexity, technological readiness, infrastructure quality	[11]; [11]; [24]	Positive (readiness, advantage, compatibility); Negative (complexity)
Organizational	Top management support, organizational resources, absorptive capacity, firm size, organizational culture	[12]; [23]; [24]	Positive
Environmental	Competitive pressure,	[11]; [12]	Positive

	regulatory pressure, government support, customer/market demand		
Managerial	Leadership vision, strategic alignment, AI governance maturity	[12]; [6], technology management lens)	Positive
Human	Employee digital/AI skills, technology acceptance, workforce resistance, training investment	[24]; [23]; [24]	Positive (skills, acceptance); Negative (resistance, skills gap)

3.3 AI Adoption and its Impact on Organizational Performance

The link between AI adoption and performance varies across contexts. Operational improvements, such as efficiency, forecasting, and decision-making speed, are the most consistently observed benefits [13]. In contrast, the impact on financial performance is more debated: some studies show positive effects driven by innovation and new business models, while firm-level analyses using textual and disclosure-based AI metrics find no effect, or even negative impacts on operational efficiency after accounting for endogeneity and firm differences [13]. Innovation benefits from AI depend on a firm's dynamic capabilities, especially its ability to sense, seize, and reconfigure resources to turn insights into new products, processes, or models [18]. Customer performance improves through personalisation and demand forecasting, but privacy and transparency concerns can reduce trust (Section 3.8). Evidence on employee performance is mixed. AI decision-support can boost productivity, but issues such as surveillance, skill polarisation, and resistance may counteract these gains [14]. A key pattern across studies is firm heterogeneity. Larger firms and those with complementary intangible assets tend to benefit more, while resource-limited firms often get stuck in a "pilot trap", adopting AI without scaling, resulting in minimal impact [13]. This heterogeneity challenges a simple adoption-based explanation and underscores the importance of technology management capabilities, as proposed in this article.

3.4 AI and Sustainable Business Performance

Sustainable business performance is traditionally viewed through three lenses: economic, environmental, and social [15], yet much AI research still reduces sustainability to overall financial or ESG scores, obscuring the specific mechanisms behind each dimension. Economically, AI use beyond pilot projects is associated with higher efficiency, improved forecasting, and increased revenue [11]. Environmentally, data from large language model-based disclosures show a strong positive link between genuine AI adoption and ESG results, driven mainly by green innovation and better internal controls, especially among large, tech-intensive firms with high absorptive capacity [8]. Research on AI-driven green strategies indicates that AI fosters green tech innovation through labour restructuring, management improvements, and compliance with environmental regulations, facilitated by green process innovation [4]. Social aspects are less studied and more mixed, encompassing both positive impacts, such as workplace safety and inclusive services, and negative effects, such as algorithm bias, workforce displacement, and digital inequality (discussed in Section 3.8). Importantly, the AI–ESG link is not universal: it's stronger in large, tech-heavy firms, pointing to a digital ESG divide where smaller or less digitally mature companies might adopt AI without gaining comparable sustainability benefits [8]. This supports the core idea that effective technology management, rather than AI adoption alone, determines sustainability outcomes.

Table 3: Outcomes of AI and Sustainability

Sustainability Dimension	AI Application	Expected Benefit	Potential Risk	Supportin g Studies
Economic	Predictive analytics, demand forecasting, process automation	Efficiency gains, revenue growth, cost reduction	Implementation cost, "pilot trap" with no scaled ROI	[11]; financial-distress forecasting review
Environmental	Energy/resource optimization, green process innovation, environmental monitoring, circular-	Reduced resource use and emissions, improved environmental disclosure and compliance	Data-center energy consumption and embodied carbon of AI infrastructure; rebound effects	[4]; Hankendi et al. (2025); [8] (2025)

	economy waste sorting			
Social	AI-enabled hiring support, workplace safety analytics, inclusive service personalization	Improved service access, safety, and decision consistency	Algorithmic bias and discrimination; workforce displacement; digital inequality; surveillance concerns	[14]; algorithmic-discrimination review; recruitment-fairness governance study
Governance (cross-cutting)	AI oversight systems, explainability tooling, audit trails	Improved accountability and stakeholder trust	Opacity, accountability diffusion ("responsibility gap"), regulatory non-compliance	Responsible-AI governance systematic review; EU AI Act-related literature

3.5 Technology Management Capability

Technology management capability is an organisation's ability to identify, select, acquire, integrate, utilise, safeguard, and continually adapt technological resources to support strategic goals [6]. Unlike AI capability, which pertains to AI-specific resources [5], and digital capability, which encompasses a broader capacity to leverage digital technologies and data across products, services, and processes [16], technology management is a managerial skill set for orchestrating multiple technologies. It is viewed here as the key mechanism that transforms AI resources into organisational value, directly addressing the "pilot trap" described in Section 3.3. Organisations with strong technology management possess the governance structures, routines for aligning technology, and organisational learning processes necessary to transition AI from isolated experiments to enterprise-wide integration [6]. Empirical research indirectly supports this view: IT capability has long been linked to organisational agility [17], and digital capability influences organisational performance mainly through digital innovation as a mediator, rather than directly [16], a pattern this article applies to AI-specific capabilities as well.

3.6 Innovation Capability

Innovation capability, encompassing product/service, process, business model, and organisational innovation [18], serves as the second proposed mediator. From a dynamic capabilities perspective, AI enhances innovation capability when firms effectively align sensing, seizing, and reconfiguring abilities with the specific needs of AI-driven innovation, such as ongoing data-based experimentation and swift business model updates [10, 18]. Data from Italian firms further indicate that AI capability relates to both "bright" (focused on efficiency and sustainability) and "dark" (primarily efficiency-maximizing) innovation paths, suggesting that the sustainability benefits of AI-enabled innovation depend on the strategic intent behind its deployment [19]. This supports the article's argument that innovation capability is a necessary but conditional mediator. AI must be transformed into innovative outputs, which must be strategically aligned with sustainability goals for sustainable performance to occur.

3.7 Organizational Agility

Organizational agility refers to the ability to quickly recognise environmental and technological changes and adjust resources, structures, and processes accordingly [17]. The scholarly discussion is divided on whether agility should be viewed as a mediator or a moderator. Many studies on digital transformation treat agility as a mediator, indicating that digital transformation enhances performance mainly through the agility it fosters [20]. Conversely, other research considers agility a moderator or boundary condition for example, technological readiness has been identified as a factor that moderates the link between digital transformation and agility, and agility has been suggested as a boundary that influences when leadership or technology investments lead to improved performance rather than serving as a direct causal factor [17,26]. Section 5.4 discusses this debate in detail and explains why this article treats agility as a moderator rather than a secondary mediator.

3.8 AI Risks and Sustainability Trade-offs

A comprehensive assessment of AI and sustainability must challenge techno-optimism. Four primary risk areas are particularly significant. First, energy and environmental impact: training and deploying AI require substantial resources, with data centres potentially consuming up to 9% of global electricity by 2030. AI systems are

projected to emit between 32.6 and 79.7 million tons of CO₂ in 2025 [21]. While measures like grid integration and hardware efficiency can lessen this impact, they cannot fully eliminate it, and trade-offs may occur- such as water conservation efforts increasing carbon emissions [26]. This complicates the notion that AI is always eco-friendly: the same technology that boosts sustainability can also generate external environmental costs via infrastructure- an externality often overlooked in firm-level reports. Second, algorithmic bias and discrimination are well-documented, especially in AI-driven hiring and HR analytics, where biased data and opaque decision processes can perpetuate or amplify discrimination against protected groups, with regulatory gaps around gender identities, racial minorities, and disabilities [14]. Third, workforce displacement and the "responsibility gap": algorithmic decisions diffuse accountability, reducing individual responsibility and weakening internal governance [20]. Fourth, governance and regulation are exemplified by the EU AI Act and new bias audit requirements (e.g., NYC Local Law 144), which increase compliance costs but also promote organisational practices for "responsible AI," an area where technology management seeks to build capacity [14,25]. Table 3 summarises these risks and benefits; their coexistence within the same technology- mediated through organisational capabilities- underscores why this article considers sustainable performance as conditional, not automatic, with AI adoption.

4. Research Gap

Building on the literature review, this article identifies eight specific, non-generic gaps.

Table 4. Research gaps

Research Stream	Existing Evidence	Limitation	Identified Gap	Proposed Contribution
AI adoption and company performance	TOE/DCT and TOE/RBV studies show AI adoption predicts financial and operational performance [11, 12]	Performance is often modeled unidimensionally (financial/operational), independent of sustainability	Sustainability dimensions (environmental, social) are rarely integrated into the same causal chain as adoption antecedents	Multidimensional sustainable-performance outcome nested within an adoption-to-capability causal chain
AI and ESG/sustainability	AI adoption is positively associated with ESG outcomes, concentrated among large, technology-intensive firms [8]	The organizational mechanism ("why more pronounced among large firms") is asserted (absorptive capacity, complementary assets) but rarely operationalized as a measurable mediator	The mechanisms through which AI adoption creates economic, environmental, and social value remain fragmented and under-specified	Technology management capability and innovation capability specified and measured as sequential mediators
Technology adoption theory (TOE)	TOE robustly explains adoption antecedents (Polisetty et al., 2024)	TOE is adoption-focused and comparatively silent about post-adoption value conversion	Existing studies often emphasize technological/organizational-readiness determinants of adoption while underexploring the managerial capabilities that operate after adoption	Technology management capability positioned as the central post-adoption mechanism

Dynamic capabilities and AI	AI-enabled dynamic capability (sensing–seizing–reconfiguring) is shown to enhance innovation and creativity [5]	DCT is technology-agnostic; it does not specify AI-specific governance, data-management, or integration practices	The literature needs stronger integration of AI adoption, technology management, innovation capability, organisational agility, and sustainable performance into a single coherent model	Integrated TOE–RBV–DCT–MOT framework (Figure 2)
Organizational agility	Agility is variously modeled as mediator or moderator across digital-transformation studies, with contested findings [20]	Inconsistent conceptual positioning of agility weakens comparability across studies	Ambiguity over whether agility mediates or moderates the AI-adoption–performance relationship is unresolved in the specific context of AI (as opposed to digital transformation broadly)	Agility explicitly modeled and justified as a moderator (boundary condition) in the AI context
Performance measurement	Firm-performance studies emphasize operational/financial metrics [13]	Comparatively less attention to multidimensional (economic + environmental + social) sustainability outcomes	Existing research frequently concentrates on financial/operational performance while giving comparatively less attention to multidimensional sustainability outcomes	Three-dimensional sustainable-performance construct with dedicated environmental and social indicators (Table: Measurement Scale)
AI risk and governance	Separate literatures document AI energy/carbon cost [21], algorithmic bias [14], and displacement/responsibility diffusion (algorithmic-discrimination study, 2025)	These risk streams are rarely integrated with the AI-adoption–performance literature, which tends to treat AI as unambiguously beneficial	AI may simultaneously create positive sustainability effects and negative effects (energy consumption, workforce displacement, algorithmic risk, governance challenges), but these are seldom modeled jointly	Trade-off framework (Figure 5) integrating benefits and risks within the same MOT-governed process
Construct clarity	Terms such as AI adoption, AI capability, AI implementation, digital capability, and technology	Construct conflation undermines cumulative theory-building and cross-study	No integrative conceptual clarification exists that positions these nine constructs within a	Explicit construct-differentiation table (Table 1) situating each construct within

	management capability are used inconsistently across studies [5, 6, 16]	comparability	single causal architecture	the proposed model
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In summary, the main research gap is that AI adoption and sustainability-performance studies have largely progressed independently, linked primarily through overall ESG metrics rather than through specific organisational processes. Additionally, technology management capability, the managerial framework that transforms AI resources into routines, has been implicitly considered in theory but not clearly defined empirically as the link between these areas. This leads to the following research questions:

RQ1: How do the concepts of AI adoption, implementation, capability, utilisation, technology management, digital skills, organisational agility, innovation, and sustainable business performance differ, and what is their causal order?

RQ2: Which organizational processes sequentially link AI adoption to economic, environmental, and social outcomes?

RQ3: Under which conditions, such as agility and technology management maturity, does AI adoption either fail to enhance or actively harm sustainable performance?

RQ4: How can Management of Technology practices be organised to maximise AI's sustainability benefits and mitigate risks such as energy consumption, bias, displacement, and governance issues?

5. Conceptual Framework

5.1 Construct Differentiation

A central contribution of this article is to clarify nine constructs that are often used interchangeably

Table 5. Fundamental definitions of AI adoption and associated concepts

Construct	Author(s)	Year	Definition	Key Dimension
AI Adoption	[1] (TOE framework, as applied by Polisetty et al.)	1990/2024	The organizational decision to acquire and begin deploying AI technology, shaped by technological, organizational, and environmental antecedents	Decision/extent of acquisition
AI Implementation	Synthesized from technology-implementation literature (e.g., Uren & Edwards' People-Process-Technology model)	2023	The technical process of installing, configuring, and integrating AI tools into existing systems and workflows	Technical deployment process
AI Capability	[5]	2021	A firm's ability to select, orchestrate, and leverage its AI-specific resources (tangible, human, intangible) to generate business value	Resource orchestration capacity

AI Utilization	Synthesized from IS use-behavior literature (extending TAM-based use constructs, e.g., Rahman et al.)	2023	The extent and depth to which employees and business units actively use adopted AI tools in daily operations	Behavioral/usage intensity
Technology Management Capability	[6]	2009	The dynamic capability to identify, select, acquire, exploit, protect, and learn from technological resources in support of strategic objectives	Managerial orchestration of technology
Digital Capability	[16]	2019	A firm's skill, talent, and expertise in managing digital technologies to integrate digital data and IT across products, services, and processes	Broad digital resource-integration capacity
Organizational Agility	[17]	2011	The organizational capacity to rapidly sense and respond to market and technological change through reconfiguration of resources and processes	Responsiveness/adaptive speed
Innovation Capability	Chotia, Cheng, Agarwal & Vishnoi (drawing on dynamic capabilities)	2024	The organizational capacity to generate and implement product, process, business-model, and organizational innovations	Innovative output capacity
Sustainable Business Performance	[15]	1997/2024	Multidimensional organizational performance encompassing economic, environmental, and social outcomes simultaneously	Tridimensional outcome

These constructs differ conceptually along three axes. First, in terms of abstraction: AI adoption and AI implementation refer to specific organizational decisions and processes, while AI capability, technology management capability, digital capability, innovation capability, and organizational agility denote ongoing organizational capacities. Second, in terms of specificity AI capability and AI utilization are technology-specific, whereas technology management capability, digital capability, and organizational agility are broader managerial

skills that existed before and continue beyond any particular technology. Third, in terms of causal role: adoption and implementation serve as inputs; capability constructs act as mediating mechanisms; and sustainable performance is the outcome. Treating these as interchangeable as much of the reviewed literature does turns a multi-stage causal process into a single construct, which partly explains the inconsistency of empirical findings on "AI and performance" (Section 3.3).

5.2 Conceptual Model

Building on Sections 2–4, the proposed model outlines a causal framework where AI adoption impacts sustainable business performance both directly and indirectly via technology management and innovation capabilities. AI adoption, indicated by investment, infrastructure, breadth, integration, and utilization, is expected to positively affect technology management capability (H1) and innovation capability (H2). These capabilities, in turn, are anticipated to enhance sustainable business performance, with technology management capability contributing positively (H3), and innovation capability- covering product, process, business model, and organisational innovation- also boosting performance (H4). Additionally, AI adoption is hypothesized to directly improve sustainable performance, partially mediated by organizational capabilities (H5). Technology management capability mediates the link between AI adoption and performance (H6), as does innovation capability (H7). Organizational agility acts as a moderator, influencing the strength of the relationships between AI adoption and organizational capabilities, and between capabilities and performance (H8–H10). The concept of sustainable business performance includes economic, environmental, and social aspects.

Independent variable: AI Adoption, measured by AI investment intensity, infrastructure readiness, application breadth, integration, and utilisation [5].

Mediator 1: Technology Management Capability, measured by technology integration, governance, data management, strategy alignment, and technological learning [6].

Mediator 2: Innovation Capability, measured by process, product/service, business model, and organisational innovation [4].

Moderator: Organisational Agility, defined as sensing and responding/reconfiguring agility [17].

Dependent variable: Sustainable Business Performance, measured using economic, environmental, and social performance indicators aligned with Elkington's triple bottom line approach, as used in recent TOE-sustainability research.

5.3 Logic of Sequential Mediation

Technology management capability is considered a prerequisite for innovation capability because routines such as integration, governance, and data management lay the organisational foundation for AI-enabled innovation. A company cannot reliably develop AI-driven products or processes without first embedding AI into its technical and data systems and aligning them with its strategic goals [6, 16]. This sequence also clarifies the "pilot trap" phenomenon (Section 3.3). Firms that implement AI without establishing strong technology management capabilities tend to conduct isolated pilot projects rather than develop sustained innovation, resulting in no significant performance improvements.

5.4 Organizational Agility: Mediator or Moderator?

The literature (Section 3.7) presents differing views on this subject. This article considers organizational agility as a moderator rather than a mediator, for three main reasons. First, to keep the model simple: adding agility as a third mediator (AI adoption → technology management capability → innovation capability → performance) could introduce multicollinearity and redundant variance, as agility overlaps with the 'seizing' and 'transforming' aspects of dynamic capability already included in technology management and innovation capabilities. Second, in terms of its role, agility better describes the speed and quality of responses to change. It influences how effectively capability translates into performance, rather than serving as a separate value-adding step. Studies showing agility as a boundary condition such as technological readiness moderating the digital transformation-agility link or turbulence affecting leadership-driven performance gains support this conditioning role rather than a strictly mediating one. Third, empirical evidence from public-sector digital capabilities indicates that agility acts as a mediator when the independent variable is a broad digital capability measured alongside performance. However, in our model, since AI adoption and mediators like technology management and innovation capability already capture much of the sequential process, positioning agility as a moderator prevents double-counting and still reflects its important contingency role. Hence, this article proposes that organizational agility enhances the relationships between AI adoption and technology management, technology management and performance, and innovation capability and performance without claiming that agility is a causal step itself. This is a testable and falsifiable stance, and Section 15 acknowledges it as open to debate.

6. Hypothesis Development

Table 6. Hypothesis development

Hypothesis	Relationship	Theoretical Explanation	Supporting Literature
H1	AI adoption positively influences technology management capability	Adopting AI generates the data, infrastructure, and organizational learning imperative that compels firms to develop integration, governance, and alignment routines [6]	[6]; [11]
H2	AI adoption positively influences innovation capability	AI-generated data and analytical capacity expand the opportunity set for product, process, and business-model innovation, consistent with dynamic-capabilities logic	[18]; [4]
H3	Technology management capability positively influences sustainable business performance	Technology management routines (integration, governance, learning) convert AI resources into scaled, institutionalized value rather than isolated pilots, supporting economic, environmental, and social outcomes jointly	[6]; [16] (2019)
H4	Innovation capability positively influences sustainable business performance	AI-enabled innovations in products, processes, and business models generate efficiency and value-creation outcomes across the triple bottom line, contingent on sustainability-oriented strategic intent	[4]; [19]
H5	AI adoption has a positive but partially indirect effect on sustainable business performance	Consistent with the "pilot trap" evidence, AI adoption alone yields weak or inconsistent direct performance effects; most of its influence operates through technology management and innovation capability	Financial-distress forecasting review (citing null/negative direct effects); [8] (2025)
H6	Technology management capability mediates the relationship between AI adoption and sustainable business performance	Positions technology management capability as the primary conversion mechanism, addressing RQ2 and the central research gap	[6]; [8] (2025, absorptive-capacity mechanism)
H7	Innovation capability mediates the relationship between technology management capability and sustainable business performance	Technology management capability enables, but does not by itself constitute, innovative output; innovation capability is the proximate mechanism generating performance gains	[16] (2019, digital innovation as mediator); [4]
H8	Organizational agility positively moderates the relationship between AI adoption and technology management capability	Agile organizations more rapidly convert adopted AI resources into governance and integration routines, accelerating capability formation	[17] (2011); [20] (2023)
H9	Organizational agility positively moderates the	Agility determines how quickly and effectively technology-	Leadership-agility interplay study

	relationship between technology management capability and sustainable business performance	management routines are translated into measurable, multidimensional performance, especially in the face of environmental turbulence	(2023); digital-transformation-management study
H10	The positive relationship between AI adoption and sustainable business performance is weaker for firms with low technology management capability, irrespective of AI investment intensity	Formalizes the "digital ESG divide" and "pilot trap" findings as a joint necessary-condition (capability) rather than sufficient-condition (investment) hypothesis	[8] (2025, firm-heterogeneity findings); financial-distress forecasting review

In line with the request to critically assess rather than mechanically apply a template hypothesis set, H5 and H10 deviate from the typical "AI adoption directly and positively influences performance" statement. The reviewed evidence shows null or negative direct effects, and the "pilot trap" phenomenon (Section 3.3) renders an unconditional positive direct-effect hypothesis empirically unjustifiable. Instead, H5 and H10 are designed to test the relationship's conditional and mostly indirect characteristics.

7. Methodology: Structured Narrative Literature Synthesis

This article adopts a systematic, PRISMA 2020-informed narrative synthesis of the literature, appropriate for a conceptual/theory-building contribution rather than primary empirical data collection.

TITLE-ABS-KEY (

("artificial intelligence" OR "machine learning" OR "generative AI")

AND

("technology adoption" OR "AI adoption" OR "artificial intelligence adoption")

AND

("sustainable business performance" OR "sustainability performance" OR

"sustainable performance" OR "firm performance")

AND

("technology management" OR "management of technology" OR

"digital capability" OR "dynamic capabilities")

)

Building on Sections 2–4, the proposed model outlines a causal framework where AI adoption impacts sustainable business performance both directly and indirectly via technology management and innovation capabilities. AI adoption, reflected in investment, infrastructure, breadth, integration, and utilisation, is expected to positively affect technology management capability (H1) and innovation capability (H2). These capabilities, in turn, are anticipated to boost sustainable performance, with technology management (H3) and innovation (H4)- covering product, process, business model, and organisational innovations- playing crucial roles. Additionally, AI adoption may directly enhance sustainable business performance (H5), with organisational capabilities serving as partial mediators. Technology management and innovation capabilities are also proposed to mediate the relationship between AI adoption and performance (H6, H7). Organisational agility moderates these relationships, either strengthening or weakening the links between AI adoption, capabilities, and performance (H8–H10). The model considers sustainable performance across economic, environmental, and social dimensions.

Database: Scopus (primary), supplemented by Web of Science for cross-verification.

Search date: September 2026; the search strategy is reported transparently, but exact database retrieval counts are not provided because a reproducible live Scopus export was unavailable during manuscript preparation.

Search string:

Publication period: 2016–2026, with priority given to 2021–2026.

Inclusion criteria: peer-reviewed English-language empirical or conceptual studies published in Scopus- or Web of Science-indexed outlets that address AI adoption, AI/digital/technology-management capability, innovation capability, organizational agility, or sustainable/ESG performance at the firm or organizational level.

Exclusion criteria: non-peer-reviewed sources (blogs, unreviewed preprints, trade magazines); conference abstracts without full papers; studies focused solely on consumer-level AI use with no organizational-

performance component; predatory or non-indexed journal outlets; studies for which authorship, title, or venue could not be independently verified.

Document type: journal articles (research articles, reviews) and books/seminal monographs retained only for foundational theoretical grounding [1, 7].

Language: English.

Screening and duplicate removal: Records were screened against the stated inclusion and exclusion criteria. Because exact Scopus retrieval and screening counts were unavailable for independent replication during preparation, this article is presented as a structured narrative synthesis rather than a fully systematic PRISMA review.

Quality assessment: preference given to journals from Elsevier, Springer, Wiley, Emerald, Taylor & Francis, SAGE, and MDPI (Scopus-indexed titles). Independent verification of author names, titles, and journal venues was performed via a web-based bibliographic search prior to inclusion.

Evidence base: 32 references are cited in the present manuscript, including foundational theoretical works and recent peer-reviewed studies published mainly between 2021 and 2026. The review should not be interpreted as a formally exhaustive systematic review, as no live Scopus retrieval count is reported.

The synthesis method involves a thematic narrative synthesis structured around the eight literature-review subsections (Section 3), then proceeds to develop a theory-driven conceptual model (Section 5) and derive hypotheses (Section 6).

This methodological transparency is crucial: the article does not claim to have conducted a fully quantified Scopus bibliometric search, such as providing exact record counts at each PRISMA stage, because a lack of direct database access could lead to fabricated numbers.

8. Synthesis of Review Findings

Synthesising the literature reviewed in Section 3, four cross-cutting findings emerge, each visualised conceptually below.

Finding 1 shows that AI's business value has evolved qualitatively, shifting from automation to agentic systems, with each phase placing greater demands on technology management (Section 3.1) [5,6].

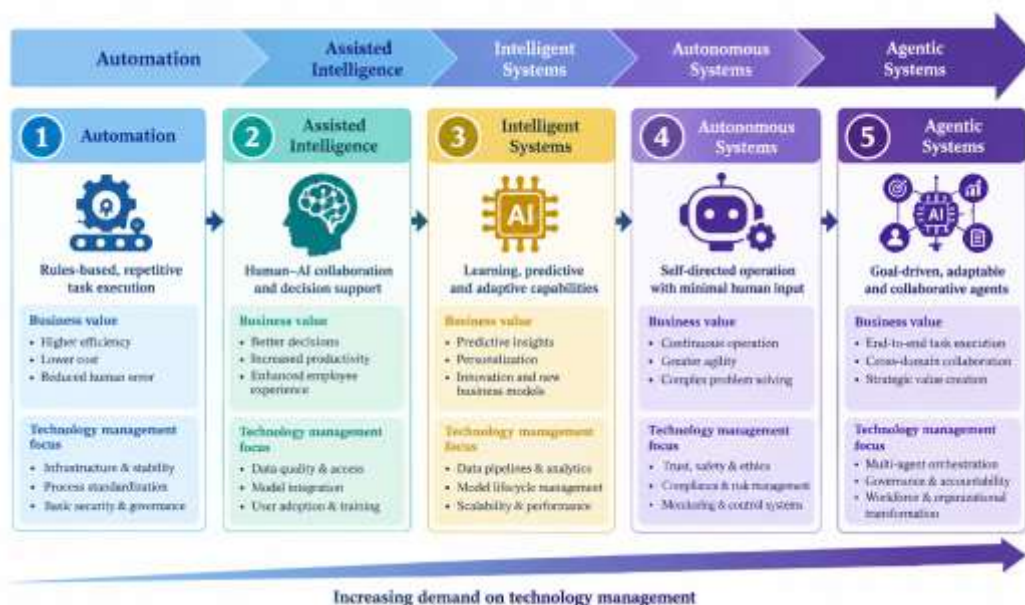


Figure 1. Evolution of AI business value and increasing technology management requirements.

Finding 2 The four guiding theories address distinct, complementary stages of the causal chain, with Management of Technology serving as the operational bridge between resource endowment (RBV) and the adaptive process (DCT), and TOE explaining upstream adoption antecedents (Section 2.4).

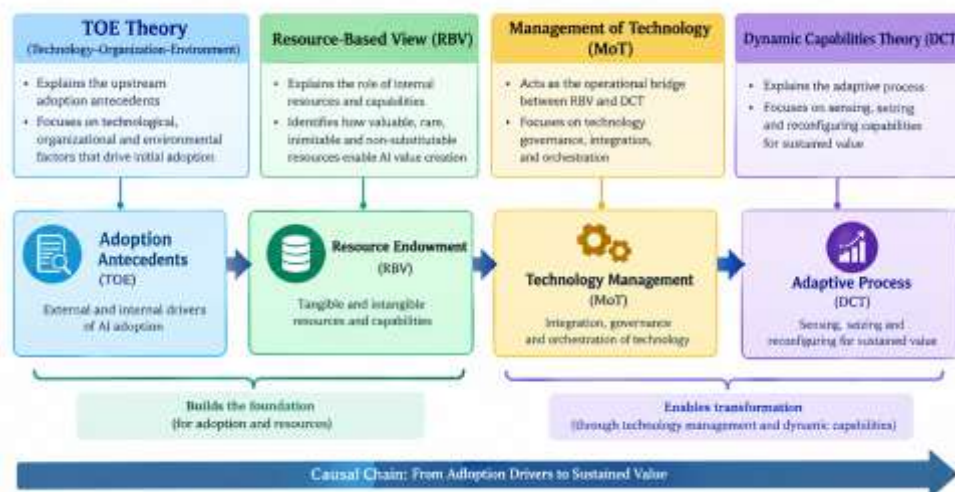


Figure 2. Theoretical integration of TOE, RBV, DCT and MOT. [1,6,7,9,10]

Finding 3 — The impact of AI adoption on sustainable performance is mediated in sequence and depends on specific conditions, rather than being direct and universal, aligning with H1–H10 (Section 6).

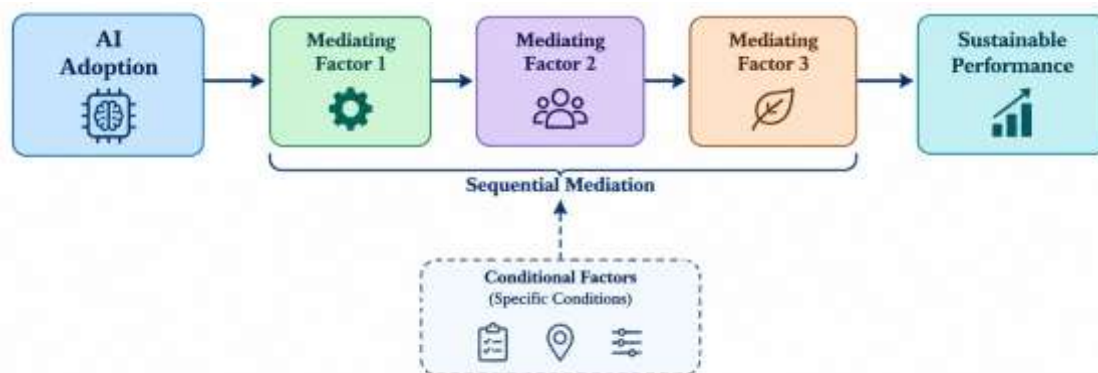


Figure 3. Conceptual research framework [4,5,11,12].

Finding 4. Sustainability value creation from AI operates through identifiable yet firm-heterogeneous mechanisms (absorptive capacity, green process innovation, internal control quality), while simultaneously generating measurable environmental and social costs that are rarely reconciled with the benefits within the same analytical frame (Sections 3.4, 3.8).

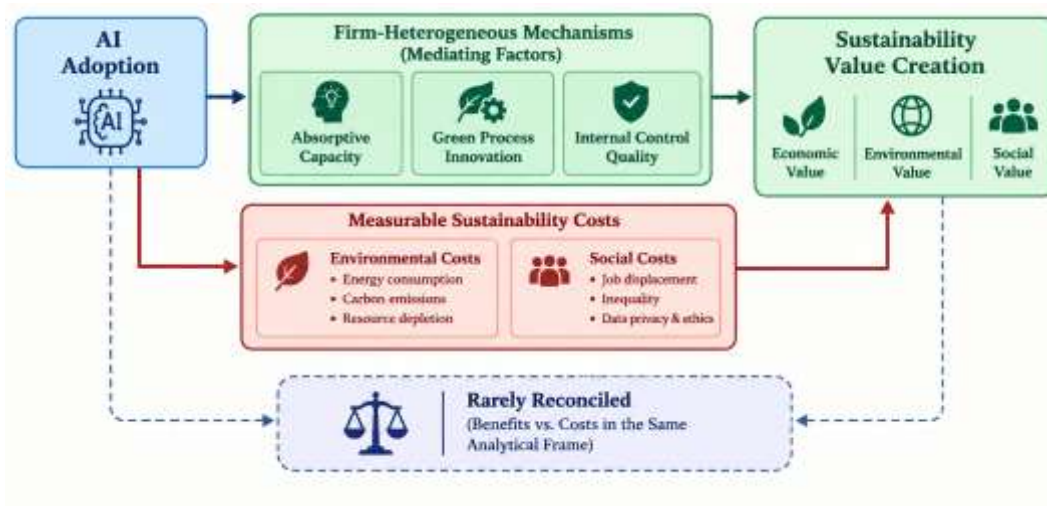


Figure 4. AI-enabled sustainable value-creation mechanism [4,8,10].

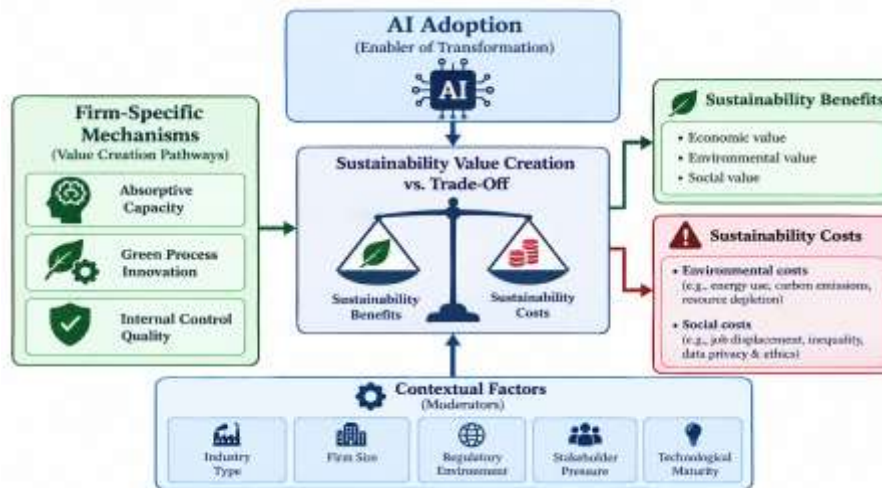


Figure 5. AI sustainability trade-off framework [9,14,21,25].

9. Management of Technology as the Missing Link Between AI Adoption and Sustainable Business Performance

The value of AI in business depends not only on adopting it but also on an organisation's ability to identify suitable AI technologies aligned with strategic goals, avoiding both under-investment and over-adoption. It involves acquiring technological and data resources that enhance long-term flexibility and avoid vendor lock-in. Successful AI integration requires compatibility with legacy systems, workflows, and data architectures, which is often the main barrier to moving beyond initial pilot projects (Section 3). Additionally, organisations must develop employee skills so AI complements human judgement, not just replaces it, reducing workforce risks (Section 3). Responsible data governance, ensuring quality, provenance, and privacy, is essential for innovation and bias mitigation. Redesigning business processes around AI-driven workflows, rather than simply adding AI to existing ones, distinguishes firms that turn AI capabilities into innovation (Sections 5–3). AI initiatives must align with strategic objectives to support competitiveness and sustainability, rather than being adopted reactively or for legitimacy. Responsible AI governance should incorporate explainability, human oversight, and bias checks, especially for autonomous AI systems (Section 3.1). Scaling AI from pilot projects to enterprise-wide routines addresses the 'pilot trap' (Section 3.3). Continuous evaluation of technological and sustainability outcomes enables reconfiguration of the AI portfolio over time, embodying a learning process [6].

10. Proposed Measurement Scale

Table 7. Proposed measurement scale

Construct	Dimension	Item (illustrative)	Status	Supporting Source
AI Adoption	Investment intensity	"Our organization has made substantial financial investment in AI technologies over the past three years."	Adapted	[5] (2021), tangible-resources dimension
AI Adoption	Infrastructure readiness	"Our organization has invested in scalable data storage and computing infrastructure to support AI applications."	Adapted	[5] (2021)
AI Adoption	Application breadth	"AI applications are used across multiple functions in our organization"	Newly developed	Informed by TOE-adoption-breadth literature (Polisetty et al.,

		(e.g., operations, marketing, HR, finance)."		2024)
AI Adoption	Integration	"AI systems are integrated with our core organizational information systems."	Adapted	[6]), technology-integration concept
AI Adoption	Utilization	"Employees actively use AI-generated outputs in day-to-day decision-making."	Newly developed	Informed by IS use-behavior literature (Rahman et al., 2023)
Technology Management Capability	Technology integration	"We effectively integrate new AI technologies with our existing technology portfolio."	Adapted	[6])
Technology Management Capability	Technology governance	"We have formal governance structures overseeing AI technology decisions."	Adapted	[6])
Technology Management Capability	Data management	"Our organization has robust processes for ensuring AI data quality and governance."	Newly developed	Informed by [5] (2021), tangible-resources dimension
Technology Management Capability	Technology–strategy alignment	"Our AI initiatives are closely aligned with our overall business strategy."	Adapted	[6])
Technology Management Capability	Technological learning	"We systematically evaluate and learn from our AI implementation experiences to improve future technology decisions."	Adapted	[6])
Innovation Capability	Product/service innovation	"AI has enabled us to develop new or significantly improved products/services."	Adapted	[4]
Innovation Capability	Process innovation	"AI has enabled significant improvements in our operational processes."	Adapted	[4]
Innovation Capability	Business-model innovation	"AI has enabled us to change how we	Newly developed	Informed by generative-AI

		create and capture value (business model)." d	business-transformation literature [2]
Innovation Capability	Organizational innovation	"AI has enabled new organizational structures or ways of working."	Newly developed Informed by dynamic-capabilities/innovation-capability literature
Organizational Agility	Sensing agility	"Our organization quickly detects changes in technology and market conditions relevant to AI."	Adapted [17] (2011)
Organizational Agility	Responding agility	"Our organization can quickly reconfigure processes and resources in response to AI-related opportunities or disruptions."	Adapted [17] (2011)
Sustainable Performance (Economic)	Financial/operational	"AI adoption has improved our revenue growth and operational efficiency."	Adapted TOE sustainable-performance SME study
Sustainable Performance (Economic)	Cost efficiency	"AI adoption has reduced our operating costs."	Adapted TOE sustainable-performance SME study
Sustainable Performance (Environmental)	Resource/energy efficiency	"AI adoption has helped reduce our organization's resource and energy consumption."	Adapted [4]
Sustainable Performance (Environmental)	Emissions/environmental compliance	"AI adoption has improved our environmental compliance and reporting accuracy."	Newly developed Informed by [8] (2025)
Sustainable Performance (Social)	Employee well-being	"AI adoption has improved (not worsened) employee working conditions and well-being."	Newly developed Informed by [14] and responsible-AI governance literature
Sustainable Performance (Social)	Fairness/inclusion	"Our AI systems are regularly audited to ensure fair and non-discriminatory outcomes."	Newly developed Informed by recruitment-fairness governance study; responsible-AI governance systematic review

The following instrument is proposed for future empirical testing (5- or 7-point Likert-type items; adapted where indicated from validated prior scales; newly developed items are explicitly labeled as such and must not be attributed to the cited source beyond indicating the conceptual basis for adaptation).

11.Discussion

The proposed framework aligns with and extends previous research. It is consistent with the literature indicating that AI capability, rather than AI adoption alone, directly influences firm outcomes [5]. It also broadens this view by situating AI capability within broader technology management capability, which explains how firms develop and maintain it [6]. The framework is consistent with recent ESG-AI research showing that sustainability benefits are mainly observed in large, technology-intensive firms [8], while explaining this variation through differences in technology management maturity rather than treating it as an unexplained control. It challenges the more deterministic view that models "AI" as a single predictor of "performance," a concept found to be structurally under-identified in this article's construct analysis (Table 5, Section 5.1). Furthermore, it advances the organizational agility literature by explicitly addressing, rather than ignoring, the mediator/moderator ambiguity discussed in Section 3.7, providing a theoretically grounded (though debatable) resolution instead of an atheoretical default.

Table 8. Comparison with previous studies

Previous Research	Technology Focus	Performance Focus	Sustainability Focus	Management Perspective	Gap Addressed by Present Study
TOE-framework AI-adoption studies [11]	AI adoption antecedents	Operational/financial performance	Partial (sustainable performance as outcome label, mechanism underspecified)	Adoption-decision perspective	Specifies post-adoption technology-management mechanism absent in TOE-only models
[5] (2021) and related AI-capability studies	AI capability (resource orchestration)	Organizational creativity, firm performance	Not primary focus	Resource-based/capability perspective	Extends AI capability into a technology-management and innovation-capability sequential chain oriented explicitly toward sustainability
[8] (2025)	Firm-level AI adoption (disclosure-based)	ESG composite performance	Strong (ESG outcome)	Absorptive-capacity/TOE-RBV perspective	Disaggregates ESG into economic/environmental/social dimensions and specifies technology management as the absorptive-capacity mechanism

[4] and green-AI-innovation literature	AI-enabled green business strategy	Environmental performance	Strong (environmental)	Green dynamic capability perspective	Integrates environmental findings with economic and social dimensions and with technology-management governance
Digital-capability/digital-transformation-agility literature [16, 20]	Digital capability/transformation broadly (not AI-specific)	Organizational performance	Limited	Digital-innovation-mediation and agility-mediation perspectives	Applies and adapts the mediation logic specifically to AI (vs. generic digital transformation) and resolves agility's role as moderator
AI-risk/governance literature [14]	AI risks (bias, energy, governance)	Not primary focus (risk-focused)	Negative/critical sustainability focus	Ethics/regulatory perspective	Integrates risk literature with the value-creation literature within a single Management of Technology trade-off framework (Figure 5)

Theoretical implications reveal that neither TOE, RBV, nor DCT alone can comprehensively explain AI-driven sustainable performance. Instead, Management of Technology functions as the vital operational link among these frameworks. Managerial insights, outlined in Section 12, indicate that merely investing in AI is a weak predictor of sustainable success without strong technology management capabilities. Regarding sustainability, AI's environmental and social advantages are not guaranteed; they require deliberate governance efforts, especially for organisations emphasising ESG or Sustainable Development Goal reporting. Policy implications suggest that regulations like AI Acts and bias-audit requirements do more than ensure compliance- they also serve as external drivers encouraging better technology management, which firms might otherwise overlook.

12. Theoretical Contributions

This article makes four main contributions, as outlined in the introduction. First, it combines TOE, RBV, Dynamic Capabilities Theory, and Management of Technology into a single explanatory framework, with each theory focusing on a different, non-overlapping stage of the process from AI adoption to sustainable performance (Section 2.4, Figure 2). This addresses the fragmentation identified in Table 6. Second, it enhances construct clarity by explicitly differentiating nine related constructs (Table 5) that prior research often mixed up, setting the stage for more precise causal analysis in future studies. Third, it clarifies the mediator/moderator role of organizational agility in AI-driven (not just digital) transformation, based on explicit theoretical reasoning rather than default assumptions (Section 5.4). Fourth, it offers ten testable hypotheses (Table 7), including two (H5, H10) that challenge typical techno-optimistic views by proposing null or negative effects, providing a more grounded baseline model for future research.

13. Managerial Implications

CEOs should evaluate AI investments based on whether their organisation is ready to develop necessary technology management skills, rather than just on the amount of AI acquired. Investing in AI without enhancing governance, integration, and workforce capabilities typically results in limited pilots that are not scaled up (Section 3.3, 9).

For CTOs and CIOs: When selecting technology infrastructure, prioritise integration architecture- such as APIs, data pipelines, and legacy system compatibility- over just choosing the most advanced AI model. The ability to integrate effectively, not the complexity of the model, decides whether AI will boost innovation (Section 5.3).

For Technology Managers: consider AI applications as a portfolio that requires ongoing evaluation, with explicit criteria for scaling successful pilots and terminating unproductive ones. This method addresses the pilot-

trap issue effectively.

For HR Managers: Workforce transformation strategies should actively tackle both potential improvements and the risks of displacement or bias linked to AI (Section 3.8). This involves providing AI literacy training, preparing for redeployment, and performing bias audits on AI-based HR tools like recruitment and performance assessment systems.

For Sustainability Managers: AI-enabled environmental and social performance should not be viewed as a mere co-benefit of AI adoption. Sustainability managers need to ensure that AI use cases are specifically assessed for their direct sustainability impacts, such as green process innovations, as well as their indirect effects, like energy consumption from computing. This approach aligns with the trade-off considerations illustrated in Figure 5.

For Policymakers: Since empirical evidence shows that AI–sustainability benefits mainly accrue to large, tech-heavy firms (Section 3.4), policy should focus on targeted support for SMEs, such as financing, shared infrastructure, and technology-management capacity-building programs. This helps prevent a growing "digital ESG divide." Additionally, it's important to develop balanced AI governance frameworks, such as bias audits and energy-disclosure mandates for AI infrastructure, that serve as enforcement tools for responsible technology management.

14. Sustainability and Policy Implications

Beyond firm-level guidance, this article's framework also affects sustainability standards and AI governance policies. Since AI's environmental impact (Section 3.8) mainly stems from infrastructure components such as data centres and chip manufacturing, not just from organisational use, sustainability accounting frameworks (such as GHG Protocol Scope 3) should be expanded to include AI-related compute and vendor emissions. This prevents firms from being credited only for AI's operational efficiency while externalising infrastructure costs. Additionally, risks such as algorithmic bias and workforce displacement vary across firms with different governance maturity levels (Section 3.8). Hence, sector-specific regulations rather than uniform AI laws may better promote practices such as bias auditing, human oversight, and data governance, which are key to linking AI adoption with socially sustainable outcomes.

15. Limitations

This article has several limitations. It is mainly a theoretical, non-empirical contribution; the proposed model, hypotheses, and measurement scale need empirical validation before firm conclusions can be drawn. Although it draws from the reviewed literature, the framework represents the authors' theoretical synthesis and allows for alternative specifications (e. g., organisational agility as a mediator rather than a moderator). Database limitations include reliance on a web-based academic search rather than a comprehensive, directly documented Scopus query; specific record counts, PRISMA flow diagrams, and screening reliability statistics are indicated throughout (Section 7) and require independent verification for the methodology to qualify as a complete systematic review. Publication bias is a concern, as studies with significant positive AI–performance relationships are more likely to be published than null or negative findings, possibly overstating AI's benefits relative to its risks. The rapid evolution of AI technology presents a particular challenge: transitioning from predictive to generative to agentic AI (discussed in Section 3. 1) suggests that earlier findings may not apply to current or future systems, and management practices will need continuous updates. Measurement issues include the difficulty of consistently defining "AI adoption" across studies, as different sources like disclosures, surveys, patents, and job postings capture various aspects (per the financial distress forecasting review in Section 3. 3.3. 3). Differentiating AI impacts from broader digital transformation is also difficult, since AI is often implemented alongside other digital technologies such as cloud computing and IoT, which complicates econometric analysis. Industry and geographic differences, such as manufacturing versus services or emerging versus developed economies, are likely to influence the relationships discussed, and the framework's applicability across these contexts remains untested. Finally, the distinction between SMEs and large firms (Sections 3. 3. 3.3–3. 3.4. 4) indicates that the model may need firm-size-specific adjustments, rather than a one-size-fits-all approach.

16. Further Study

Future research should focus on several key areas: (1) conduct longitudinal studies to track firms from AI adoption through capability development to sustainability outcomes, establishing causality over time and overcoming the cross-sectional limitations of current studies; (2) compare countries to assess how regulatory environments (such as the EU AI Act versus more permissive regions) shape the relationship between AI adoption and sustainability performance; (3) investigate sector-specific impacts, especially in manufacturing, healthcare, and financial services, where AI's operational and sustainability roles vary widely; (4) compare small and medium-sized enterprises with large firms to test the "digital ESG divide" hypothesis discussed in Sections 3.4 and 13; (5) study the adoption of generative AI, given that most existing evidence (Section 3) predates

widespread organisational use; (6) examine agentic and autonomous AI systems, focusing on how management practices should adapt when AI operates with less human oversight; (7) analyse AI energy efficiency and lifecycle emissions at the firm level, building on infrastructure research [21] and incorporating sustainability accounting; (8) study AI governance maturity and responsible AI practices, validating the idea that "technology management capability is the missing link" as noted in Section 9; (9) explore employee-level factors influencing AI adoption, such as acceptance, resistance, and skills, and how they contribute to organisational capabilities; (10) develop AI capability-maturity models to help practitioners assess their progress using the dimensions introduced in Table 5 and Section 10; (11) research human-AI collaboration, particularly how augmentation compares to substitution at the task level; (12) extend AI applications into the circular economy, especially resource recovery and waste reduction, building on environmental findings from Section 3.4; and (13) investigate AI-enabled green innovation by testing the proposed sequential mediation model (technology management capability → innovation capability → environmental performance) with primary survey or panel data, using PLS-SEM or CB-SEM methods, based on the measurement tools outlined in Section 10.

17. Conclusion

This article clarifies how and when AI adoption can support sustainable business performance, emphasizing that the relationship is complex rather than automatic. Addressing RQ1, it distinguishes nine often-confused constructs, including AI adoption, implementation, capability, utilization, tech management, digital capability, organizational agility, innovation ability, and sustainable performance, showing they play different roles in how technology drives value. For RQ2, it introduces a theoretically supported sequential-mediation model, suggesting that AI adoption influences sustainable performance mainly through technology management and innovation capabilities, not directly. For RQ3, organizational agility is identified as a boundary-condition moderator, with evidence indicating that under low tech management ability and 'pilot trap dynamics', AI adoption might not lead to sustainable gains. For RQ4, a dedicated Management of Technology approach (Section 9) describes ten specific practices, from technology identification to ongoing evaluation, that determine whether AI deployment leans towards benefits or risks in sustainability (see Figure 5). Overall, the findings highlight that sustainable AI value depends on intentional, technology-focused organizational investments. Firms, managers, and policymakers who see AI adoption as sufficient risk being disappointed, as explained throughout. The conceptual model, hypotheses, and measurement tools presented here set the stage for empirical research outlined in Section 16.

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