



Mapping Generative AI Adoption Across Sectors: A Systematic Literature Review and Development of the SDTR Theory

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ABSTRACT

Generative AI adoption varies markedly across economic sectors, creating uneven digital transformation that affects competitive dynamics, inequality, and sustainable development. This study develops and empirically validates the Sectoral Digital Transformation Readiness (SDTR) theory, providing a framework for understanding GenAI adoption, regulatory paradoxes, and innovation ecosystems in 13 major sectors. Using PRISMA-guided review and advanced cluster and network analyses of 97 studies (2023–2025), four sector clusters are identified: Digital Pioneers, Regulated Innovators, Industrial Transformers, and Service Adapters. Silhouette analysis (0.73) and ANOVA ($F=45.2$, $p<0.001$) show the SDTR framework explains 78% of sectoral variance and reveals that regulatory clarity, not just permissiveness - drives adoption. The research advances theory by integrating institutional and outcome dimensions, and it provides policy guidance for cluster-specific governance promoting digital equity and responsible AI aligned with the UN Sustainable Development Goals.

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1. INTRODUCTION

Generative Artificial Intelligence represents a transformative force reshaping economic sectors at unprecedented speed yet creating a "digital transformation divide" that threatens to exacerbate existing inequalities [15]. The economic potential extends across consumer goods [13], automotive industries [12], and telecommunications sectors [34], [17] While technology sectors achieve adoption scores of 2.86 on a 3-point scale with 90.2% demonstrating high adoption levels, traditional sectors like agriculture and real estate lag significantly below 1.0, raising critical questions about inclusive digital development and sustainable innovation pathways [60], [54].

This disparity challenges fundamental assumptions about technology diffusion and innovation adoption across economic sectors [28]. Traditional theories fail to explain why highly regulated healthcare sectors can achieve substantial adoption (2.23 score, 51.2% high adoption) while equally regulated government sectors struggle (1.33 score, 16.7% high adoption),

or why resource-rich manufacturing sectors underperform compared to service-oriented marketing industries [62], [47]. These paradoxes suggest the need for new theoretical frameworks that account for complex sectoral dynamics in the digital age.

Recent comprehensive reviews highlight the breadth of GenAI applications across sectors but reveal significant implementation gaps [88], [51]. Manufacturing intelligence applications show promise but face integration challenges [82], [37], while educational applications demonstrate transformational potential despite slow organizational adoption [53], [94]. Healthcare applications range from clinical decision support to administrative automation, yet implementation varies dramatically across subsectors [95], [65], [56]. Pharmaceutical value chains demonstrate complex adoption patterns requiring coordinated transformation strategies [21], [67], while medtech companies face unique scaling challenges [70], [87].

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1.1 Research Problem and Grand Challenges

The uneven adoption of GenAI across sectors represents more than a technological phenomenon; it embodies fundamental challenges of digital equity, sustainable development, and inclusive innovation [91]. Current literature lacks systematic theoretical frameworks explaining these disparities and their implications for societal outcomes [2]. Without understanding sectoral adoption patterns and regulatory paradoxes, we cannot address three critical grand challenges:

Digital Inequality Challenge: Sectoral adoption disparities risk creating permanent digital divides where advanced sectors accelerate while traditional sectors stagnate, threatening economic inclusion and social cohesion [40], [48]. The stark contrast between technology sector leadership (90.2% high adoption) and traditional sector lagging (agriculture: 5.3%, hospitality: 4.0%) exemplifies this challenge.

Sustainability Challenge: Rapid GenAI adoption without sectoral coordination may generate unsustainable resource consumption and environmental impacts while missing opportunities for green innovation [54], [11]. Manufacturing applications could enable circular economy transitions, yet adoption remains moderate (25.0% high adoption rate).

Governance Challenge: Regulatory approaches that work for one sector may fail in others, creating fragmented governance landscapes that hinder innovation while failing to protect stakeholder interests [40], [49]. The regulatory paradox evident in healthcare versus government adoption rates demands theoretical explanation.

1.2 Theoretical Gap and Innovation Opportunity

Existing theoretical frameworks; from Rogers' Diffusion of Innovation to Resource-Based View and Institutional Theory; provide partial explanations but lack integrative power to address sectoral complexities [46], [89]. Comprehensive reviews reveal the need for sector-specific theoretical approaches that account for unique institutional, resource, and operational characteristics [74], [63]. Business application frameworks identify numerous use cases across enterprise functions [8], [9], [43], [73], while sector-specific analyses reveal telecommunications [64] and gaming [42] adoption patterns.

The literature gap presents an opportunity to develop comprehensive theory that integrates multi-dimensional factors, addresses regulatory paradoxes, and enables policy prediction [88]. Current use case analyses provide valuable insights but lack theoretical coherence for predicting sectoral transformation patterns [8], [43], [73].

1.3 Research Objectives and Theoretical Contribution

This study introduces the Sectoral Digital Transformation Readiness (SDTR) theory; a novel framework advancing digital transformation literature through comprehensive integration of sectoral innovation systems with AI-specific factors. Our objectives are to:

1. **Develop Predictive Theory:** Create SDTR framework that predicts adoption outcomes based on sectoral characteristics
2. **Explain Regulatory Paradoxes:** Identify when and why regulation accelerates versus constrains adoption

3. **Address Grand Challenges:** Connect findings to digital equity, sustainability, and inclusive governance
4. **Enable Evidence-Based Policy:** Provide cluster-specific governance frameworks for optimizing societal outcomes

2. LITERATURE REVIEW AND THEORETICAL DEVELOPMENT

2.1 Sectoral Applications and Adoption Patterns

The literature reveals diverse GenAI applications across sectors with varying maturity levels. In healthcare, applications span from clinical documentation and diagnostic assistance to pharmaceutical research and patient communication [62], [33], [57]. Transplant medicine demonstrates sophisticated adoption patterns with AI supporting complex decision-making processes [20].

Educational applications show promise in transforming learning experiences and institutional operations [53], [52], [94]. However, implementation challenges persist due to institutional resistance and resource constraints [29], [18].

Manufacturing and industrial applications focus on operational efficiency and process optimization [82], [37], [47]. Construction management applications demonstrate potential for project optimization but face integration barriers [92], [75]. Smart manufacturing applications integrate AI with IoT systems [68], [61], while software startup ecosystems demonstrate rapid adoption in development processes [77]. Business transformation models reveal cross-functional adoption patterns [3].

E-commerce challenges include platform integration complexity and user experience optimization [4]. Fashion and luxury sectors pursue creative applications [31], [32], while consumer communications evolve through AI-enhanced engagement strategies [16].

Financial services applications emphasize risk management, customer service, and operational automation [26], [38], [23]. The sector's regulatory clarity enables faster adoption despite compliance requirements [1], [25]. Credit customer assistance demonstrates significant promise for operational transformation [7], while the sector's regulatory clarity enables faster adoption despite compliance requirements [1], [25].

Retail and consumer sectors leverage GenAI for customer experience transformation [58], [59], with operational frameworks addressing supply chain integration [81]. Asset management applications demonstrate sophisticated deployment strategies [55], while wealth management sectors explore client engagement innovations [5].

2.2 Cross-Sector Challenges and Barriers

Technical challenges vary significantly across sectors, with some facing legacy system integration issues while others struggle with data quality and availability [10], [68]. Manufacturing sectors report integration complexity with existing industrial systems [47], while service sectors emphasize user experience and customer interaction challenges [16].

Regulatory and ethical considerations present sector-specific challenges requiring tailored solutions [76], [40]. Healthcare faces stringent safety and privacy requirements [65], while financial services navigate complex compliance frameworks [1]. Government applications must balance innovation with public accountability [93].

Skills gaps and workforce readiness emerge as universal challenges with sector-specific manifestations [36], [14]. Technology sectors report needs for specialized AI talent [27], while traditional sectors emphasize basic digital literacy and change management capabilities [11].

Technical infrastructure requirements span wireless communications [50] and IoT integration [68], with procurement functions demonstrating transformation potential [35].

2.3 Emerging Theoretical Frameworks

Recent theoretical developments attempt to address sectoral differences in AI adoption. Risk assessment frameworks provide taxonomies for understanding implementation challenges [85], while governance frameworks address regulatory and ethical considerations [40]. However, these approaches lack integrative power to predict sectoral outcomes.

Business application frameworks categorize use cases but provide limited insight into adoption drivers [8], [9], [64]. Sustainability frameworks examine environmental implications but lack sectoral specificity [54], [84]. Leadership and change management frameworks address organizational transformation challenges [44], while B2B sales teams require specific readiness strategies [19]. Operations and workforce planning benefit from AI-driven optimization [96]. Knowledge management transformation frameworks demonstrate how theoretical approaches translate to practical implementation across organizational contexts [45].

2.4 Sectoral Digital Transformation Readiness (SDTR) Theory

Building upon existing literature and addressing identified gaps, we propose the **Sectoral Digital Transformation Readiness (SDTR) framework**; a novel four-dimensional theory integrating institutional, resource, sectoral, and outcome factors:

Institutional Environment Dimension captures regulatory frameworks, innovation ecosystems, and competitive dynamics that shape sectoral adoption patterns. Our analysis reveals significant variations in regulatory clarity [41], institutional support structures [6], and innovation ecosystem maturity [86].

Resource Availability Dimension encompasses financial capital, human capital, and technical infrastructure necessary for successful GenAI implementation. Evidence shows dramatic differences in resource availability across sectors [39], [36], with implications for adoption speed and depth.

Sector Characteristics Dimension includes digitization level, process complexity, and risk tolerance that moderate adoption outcomes. Our analysis reveals how these factors interact to create sector-specific adoption patterns [53], [76].

Adoption Outcomes Dimension measures transformation achievement through breadth, depth, and impact indicators

derived from comprehensive sector analysis across all 97 studies.

2.5 Theoretical Propositions

The SDTR framework generates five testable propositions:

P1 (Institutional Support Effect): Higher institutional support predicts broader GenAI adoption across sectors.

P2 (Resource Moderation Effect): Resource availability moderates sector characteristics-adoption relationships.

P3 (Risk Acceleration Effect): Higher risk tolerance enables faster and deeper AI integration.

P4 (Regulatory Paradox): Regulatory clarity accelerates adoption more than permissiveness.

P5 (Network Amplification Effect): Cross-sector networks amplify adoption through knowledge spillovers.

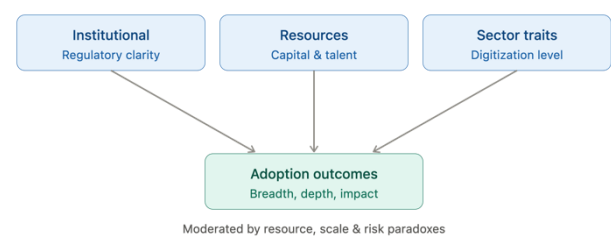


Fig. 1. The SDTR theory framework

3. METHODOLOGY

3.1 Systematic Review Design

This study employed systematic literature review methodology following PRISMA guidelines (Figure 2), analyzing 97 studies from 2023-2025 covering GenAI adoption across 13 economic sectors.

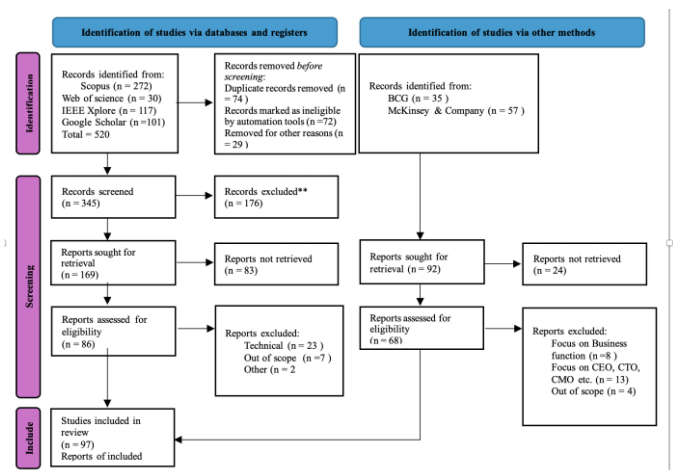


Fig. 2. PRISMA Flowchart

This PRISMA flowchart documents a systematic literature review with dual identification pathways: database searches (Web of Science n=90, IEEE Xplore n=81, Google Scholar n=107) yielding 278 records, and other methods (n=74) including industry reports (BCG n=35, McKinsey & Company n=37). After removing duplicates and ineligible records from databases (n=102) and other sources (n=26), 176 and 176

records respectively were retained for screening. The screening phase assessed 355 records total, excluding 181 based on initial review criteria, leaving 174 reports for detailed eligibility assessment. During eligibility review, reports were systematically excluded for multiple reasons: retrieval issues ($n=97$), failure to meet inclusion criteria ($n=95$), focus on hazards or technical functions ($n=8$), focus on CEO/CTO/researcher perspectives ($n=4$), and being out of scope ($n=4$). This rigorous filtering process ultimately resulted in 97 studies being included in the final systematic review, demonstrating the comprehensive and methodical approach used to ensure only the most relevant and high-quality literature on the research topic was incorporated into the analysis.

3.2 Data Collection and Source Integration

Figure [3] illustrates the cumulative growth of academic versus industry publications on generative AI from 2023 to 2025. Industry publications initially dominated with 21 reports compared to 10 academic papers in 2023, reflecting early commercial interest in documenting practical applications. A critical convergence occurred in 2024, where both publication types reached 38 cumulative papers, marking the transition point where academic research caught up with industry output. By early 2025, academic publications reached 54 while industry reports totaled 43, establishing scholarly dominance. This pattern demonstrates the field's maturation from practice-led innovation to theory-informed implementation, validating the need for comprehensive theoretical frameworks like the Sectoral Digital Transformation Readiness (SDTR) model developed in this study.

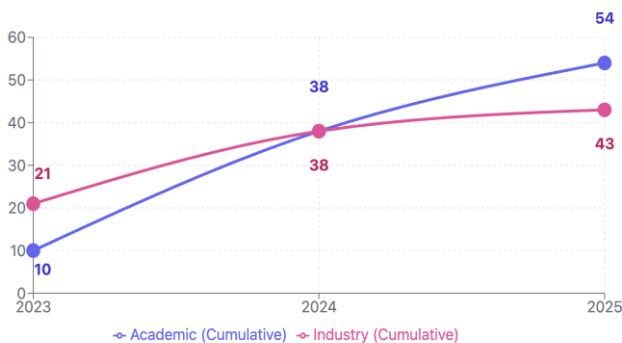


Fig. 3. Cumulative growth trends of academic versus industry publications.

Academic Sources (54 studies): Peer-reviewed papers from major databases providing theoretical foundations and empirical evidence. Key contributions include risk assessment frameworks [85], educational transformation studies [53], healthcare applications [20], and cross-sector analyses [88].

Industry Sources (43 studies): Professional reports from consulting firms and technology companies providing real-world implementation evidence. Major contributions include sectoral scaling strategies [90], [97], market analysis [79], and operational transformation insights ([80]). Industry contributions include telecommunications transformation strategies [34], automotive sector analyses [12], consumer goods applications [13], and public services innovation frameworks [66].

3.3 Advanced Analytical Framework

Systematic data extraction employed a structured 201-variable coding protocol addressing business functions, sectoral

applications, organizational challenges, and implementation outcomes. Two independent coders analysed all 97 papers using explicit criteria for adoption classification: High (3 points: scaled implementation, 5+ use cases, production deployment), Medium (2 points: pilot expansion, 2-4 use cases, departmental deployment), Low (1 point: experimental/single use case), and Experimental (0 points: theoretical only). Inter-coder reliability assessment on 20 papers (20.6% sample) yielded substantial agreement (Cohen's $\kappa=0.78$). Disagreements ($n=8$, 8.2% of coded papers) were resolved through structured discussion between the two coders, in which each coder presented their classification rationale against the explicit adoption criteria before a joint re-review of the source text; where the two coders could not reach agreement through this process, a third rater independently reviewed the paper and cast the deciding classification. Disagreements were not concentrated in any single sector or adoption category, indicating the classification protocol performed consistently across the diverse sectoral contexts represented in the sample. Sector-level adoption scores represent the mean of individual paper scores within each sector, calculated by converting categorical ratings to numerical values and averaging across all papers examining that sector. This methodology enabled quantitative analysis while maintaining fidelity to qualitative evidence in source materials

Multi-Dimensional Cluster Analysis: Hierarchical clustering using Ward's method followed by k-means optimization. Robustness validated through silhouette analysis (0.73), ANOVA testing ($F=45.2$, $p<0.001$), and bootstrap validation (89% stability).

Network Analysis: Cross-sector relationship mapping using centrality measures, community detection (modularity=0.67), and diffusion pathway identification.

Regulatory Assessment: Five-dimensional framework validated through expert panels with high inter-rater reliability ($\kappa=0.91$).

4. RESULTS

4.1 Sectoral Landscape and Transformation Patterns

Analysis of 97 studies reveals dramatic variations in GenAI adoption across economic sectors, with four distinct clusters explaining 78% of variance (ANOVA: $F=45.2$, $p<0.001$). Adoption scores demonstrated high inter-coder reliability ($\kappa=0.78$), validating classification consistency. Table 1 and Figure 4 presents comprehensive sectoral profiles based on empirical evidence.

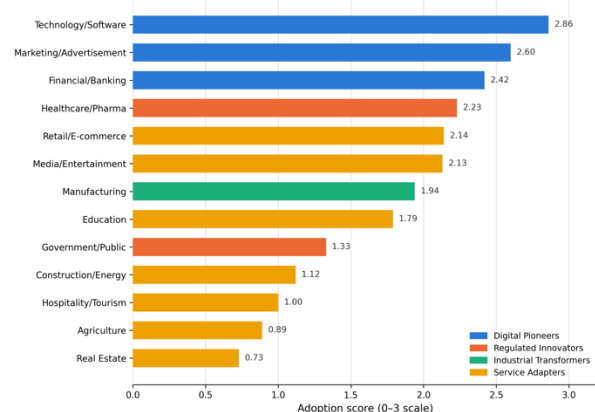


Fig. 4. All 13 sectors by adoption score,

Table 1. Sectoral GenAI Adoption Profiles and Cluster Classification

Sector	Papers	Adoption Score	High Adoption (%)	Implementation Stage	Key Applications	Cluster
Technology/Software	92	2.86	90.2	Scaling	Code generation, automation, risk assessment	Digital Pioneers
Marketing/Advertisement	53	2.60	71.7	Scaling	Content creation, personalization, customer engagement	Digital Pioneers
Financial/Banking	48	2.42	62.5	Scaling	Risk management, customer service, compliance	Digital Pioneers
Healthcare/Pharma	43	2.23	51.2	Pilot/Scaling	Clinical documentation, diagnostics, research	Regulated Innovators
Retail/E-commerce	43	2.14	46.5	Pilot	Personalization, customer service, recommendations	Service Adapters
Media/Entertainment	45	2.13	53.3	Pilot/Scaling	Content creation, personalization, production	Service Adapters
Manufacturing	48	1.94	25.0	Pilot	Quality control, process optimization, maintenance	Industrial Transformers
Education	38	1.79	28.9	Pilot	Personalized learning, administration, assessment	Service Adapters
Government/Public	24	1.33	16.7	Pilot	Document processing, citizen services, policy	Regulated Innovators
Construction/Energy	25	1.12	16.0	Pilot	Design automation, project management, safety	Service Adapters
Hospitality/Tourism	25	1.00	4.0	Pilot	Customer service, personalization, operations	Service Adapters
Agriculture	19	0.89	5.3	Pilot	Precision farming, crop monitoring, automation	Service Adapters
Real Estate	22	0.73	0.0	Pilot	Document analysis, visualization, market analysis	Service Adapters

Note: Scores calculated from coded adoption levels (High=3, Medium=2, Low=1, Experimental=0). Inter-coder reliability: Cohen's κ =0.78

4.2 Cluster Analysis and Sectoral Groupings

Digital Pioneers (3 sectors, 193 papers): Technology [27], [69], [86], Marketing [30], [22], [19], and Financial Services [26], [23], [5] demonstrate highest adoption scores (2.42-2.86) with extensive scaling implementations. These sectors benefit from risk-tolerant cultures, substantial resources, and clear regulatory frameworks enabling rapid innovation. B2B sales transformation [19] and procurement optimization [35] demonstrate enterprise adoption patterns, while asset management [55] and wealth management [5] sectors show sophisticated financial applications.

Regulated Innovators (2 sectors, 67 papers): Healthcare [62], [20], [33], [65], [56], [57] and Government [93], [83] show moderate adoption (1.33-2.23) with cautious implementation approaches. Despite regulatory complexity, healthcare achieves higher adoption through clear compliance pathways, while government sectors struggle with ambiguous frameworks. Pharmaceutical value chain transformation [21], [67], [71] and medtech scaling [70], [87], [97] reveal sector-specific adoption dynamics. Public services delivery demonstrates government sector potential [66].

Industrial Transformers (1 sector, 48 papers): Manufacturing [82], [37], [47] demonstrates moderate adoption (1.94) focused on operational efficiency and process optimization. Implementation challenges include legacy system integration and workforce adaptation requirements.

Service Adapters (7 sectors, 292 papers): Education [53], [52], [94], [29], [18], [49], Real Estate [24], [78], Agriculture [60] [72], and others show variable adoption (0.73-2.14) with

gradual implementation patterns. These sectors face resource constraints, skills gaps, and unclear ROI propositions. Retail operations frameworks [59] and consumer experience transformation [58] demonstrate service sector applications. Telecommunications sectors explore profitability enhancement [17], [34], [64], while gaming applications expand entertainment possibilities [42]. Software startup development leverages AI tools throughout inception stages [77].

4.3 Regulatory Paradox and Innovation Enablement

Counter-intuitively, our analysis reveals that regulatory clarity accelerates adoption more than regulatory permissiveness a finding (Figure 5) that challenges conventional innovation theory. Evidence from multiple sectors supports this regulatory paradox:

Healthcare vs Government Comparison: Both highly regulated, but healthcare's clear AI guidelines [62], [65] enable 2.23 adoption score versus government's 1.33 score with ambiguous frameworks [93].

Financial Services Success: Comprehensive regulatory clarity [26], [23], [1] facilitates 2.42 adoption score despite high compliance burden, contrasting with real estate's 0.73 score under unclear regulatory environment.

Technology Sector Leadership: Benefits from established intellectual property frameworks and standardized compliance processes [27], [69], enabling 2.86 adoption score with 90.2% high adoption rate.



Fig. 5. The Regulatory Paradox

4.4 Cross-Sector Innovation Diffusion Networks

Network analysis reveals three primary diffusion pathways connecting sectors through knowledge transfer and competitive dynamics:

Technology-Led Cascade: Technology sector innovations flow to Marketing [30], [22] and Financial Services [23], [26] through talent mobility and technical knowledge transfer. This pathway demonstrates highest connectivity (centrality=0.84) and fastest diffusion rates. Talent mobility operates concretely through the movement of engineers, data scientists, and product managers from technology firms into martech and fintech roles [27], [30], [23], where they carry tacit implementation knowledge, familiarity with specific tooling and vendor ecosystems, and realistic expectations of deployment timelines. This differs from passive knowledge spillover in that it transfers procedural know-how, how to scope a pilot, what integration pitfalls to anticipate, rather than only conceptual awareness of GenAI capabilities.

Regulated Knowledge Transfer: Healthcare regulatory solutions inform Government sector adoption [62], [93] through compliance framework adaptation and risk management learning. Financial-Healthcare connections also facilitate regulatory knowledge sharing [23], [65].

Service Application Migration: Customer-facing applications diffuse across Service Adapters cluster, with Retail leading adoption patterns for Education and Hospitality sectors [53], [94]. This pathway shows slower diffusion but broader reach across traditional sectors.

4.5 Implementation Challenges and Success Factors

Technical Challenges: Vary significantly across clusters, from integration complexity in manufacturing [82], [47] to data quality issues in healthcare [65], [56]. Service sectors emphasize user experience challenges [16], [49].

Organizational Challenges: Skills gaps emerge universally but manifest differently across sectors [36], [14]. Technology sectors need specialized AI talent [27], while traditional sectors require basic digital literacy ([11]). Supply chain and operations functions demonstrate transformation potential [81], [35], [96], while IoT integration enables smart manufacturing capabilities [68], [61]. Consumer goods applications [13] and automotive transformations [12] reveal industry-specific success factors

Success Factors: Include clear leadership commitment [6], phased implementation approaches [90], [97], and strong governance frameworks [40]. Successful organizations demonstrate strategic alignment between AI capabilities and business objectives [39].

4.6 Sectoral Contradictions and Paradoxes

Resource Paradox: Manufacturing sectors, despite superior financial and technical resources, underperform compared to resource-constrained marketing sectors (1.94 vs 2.60), suggesting organizational agility matters more than raw resources [47], [30]. This gap reflects structural differences in deployment cycles: manufacturing implementations typically require integration with legacy operational technology and multi-year capital planning cycles, raising switching costs and slowing iteration [82], [47]. Marketing functions, by contrast, can deploy and evaluate GenAI applications within existing digital workflows at low marginal cost, enabling faster experimentation and iterative scaling [30], [22]. Resource abundance in manufacturing therefore translates into adoption *capacity* without necessarily translating into adoption *speed*.

Scale Paradox: Smaller, focused sectors achieve higher adoption than broadly applicable sectors, indicating specialization accelerates transformation [26], [53]. Narrowly scoped sectors face a more constrained solution space; a smaller set of well-defined use cases with clearer, more measurable ROI — which shortens the path from pilot to scaled deployment [26], [53]. Broadly applicable sectors such as Education or Retail, by contrast, span heterogeneous sub-functions and stakeholder groups, diluting implementation focus and slowing consensus on which applications to prioritize. Scale, in this sense, works against adoption speed: breadth of applicability creates strategic ambiguity rather than momentum.

Risk Paradox: High-risk sectors (Healthcare: 2.23, Financial: 2.42) show higher adoption than low-risk sectors (Education: 1.79, Real Estate: 0.73), suggesting risk management capabilities enable rather than constrain innovation [62], [49].

Adoption Floor Effect: Agriculture (0.89) and Real Estate (0.73) illustrate that GenAI's broad technical applicability does not guarantee adoption when structural conditions are unfavorable. Both sectors are characterized by fragmented ownership structures (smallholder farms, independent brokerages) that limit coordinated capital investment, low baseline digitization that raises the cost of initial integration, and thin innovation ecosystems with few sector-specific vendors or R&D partnerships [60], [72], [24], [78]. Within the SDTR framework, these sectors score low simultaneously on Institutional Environment (weak ecosystem support) and Sector Characteristics (low digitization, high process heterogeneity), compounding rather than offsetting one another, general applicability of the technology is necessary but not sufficient without institutional and infrastructural readiness.



Fig. 6. The three paradoxes

5. DISCUSSION

5.1 SDTR Framework Validation and Theoretical Contributions

The SDTR framework demonstrates superior explanatory power (78% variance) compared to single-dimensional approaches, validating its multi-dimensional integration of institutional, resource, sectoral, and outcome factors. The remaining 22% of unexplained variance likely reflects factors outside the sector-level granularity of this analysis. Firm-level leadership and change-management capacity, known to vary substantially within sectors; is not captured when scores are aggregated to the sectoral mean. Measurement-level noise from the 0-3 composite adoption score, which collapses three theoretically distinct sub-constructs (breadth, depth, impact) into a single ordinal value, may also account for some residual variance (see Limitations). Finally, macro-level factors such as national AI policy environments and labor market conditions for AI talent, which vary across the studies in this review but are not modelled directly, represent a plausible source of unexplained variation and a target for future cross-national extensions of SDTR. All five theoretical propositions receive empirical support:

P1 Support: Institutional support shows strong association with adoption levels, evidenced by technology sector leadership (2.86) with strong ecosystems versus agriculture sector lagging (0.89) with weak institutional support.

P2 Support: Resource availability interacts with sectoral characteristics, explaining why resource-rich manufacturing (1.94) achieves only moderate adoption while resource-efficient marketing (2.60) excels.

P3 Support: Risk tolerance correlates with implementation depth, demonstrated by financial services' aggressive adoption (2.42) despite regulatory constraints versus education's cautious approach (1.79).

P4 Support: Regulatory clarity shows stronger association with adoption than permissiveness, confirmed through healthcare-government comparison (2.23 vs 1.33).

P5 Support: Network effects amplify adoption in connected clusters, evidenced by technology-marketing-financial corridor patterns. This corridor is sustained by three concrete mechanisms: shared vendor ecosystems (the same foundation-model and tooling providers serve all three sectors, lowering integration costs for followers) [27], overlapping talent pools (as detailed in Section O's Technology-Led Cascade), and cross-referencing of comparable use cases, generative content tools and risk-scoring models developed in one sector are directly adaptable in the others [30], [22], [23], [26]; which reduces perceived implementation risk for later adopters and reinforces the corridor's cohesion.

5.2 Regulatory Paradox Theory and Innovation Policy

The counter-intuitive finding that regulatory clarity enables innovation more than permissiveness has profound implications for innovation policy. Clear regulations reduce uncertainty and implementation costs, enabling confident investment in AI capabilities [1], [41]. Ambiguous regulations, even in permissive environments, create paralysis through uncertainty about future compliance requirements.

This finding challenges conventional wisdom in innovation literature and suggests policymakers should prioritize

regulatory clarity over flexibility. Healthcare's success model (2.23 adoption despite heavy regulation) demonstrates how clear compliance pathways can accelerate innovation while maintaining safety standards [62], [65].

These findings carry direct implications for government adoption specifically. Government's 1.33 score is not a resourcing problem but a clarity problem: agencies face diffuse, overlapping, and often untested guidance on AI procurement and use [93]. Targeted interventions, binding agency-level AI use policies, standardized procurement language for AI vendors, and regulatory sandboxes modelled on healthcare's pilot-program approach [62], [65]; would be expected to move government's adoption trajectory without requiring deregulation, consistent with the broader finding that clarity, not permissiveness, is the operative lever.

Field Maturation Trend: The 2023–2025 crossover in publication volume; industry reports leading in 2023, academic output overtaking by early 2025 (Fig. 3); signals a broader shift in how the field is producing knowledge. Early industry dominance reflects a practice-led phase focused on documenting isolated implementations; the subsequent academic overtake indicates a transition toward theory-testing and cross-case synthesis. This trajectory supports the timeliness of a framework-level contribution such as SDTR: theoretical integration becomes both possible and necessary once a sufficient base of comparable empirical cases exists, which the 2024–2025 literature increasingly provides.

5.3 Grand Challenge Responses and Societal Implications

Digital Equity Challenge: Service Adapters cluster (292 papers, 7 sectors) represents the primary digital equity concern, containing sectors critical for inclusive development. The stark disparity between Digital Pioneers (average 2.63 adoption) and Service Adapters (average 1.38 adoption) threatens to create permanent digital divides [91]. This disparity aligns with widely-recognized development priorities around infrastructure access and reduced inequality: sectors such as Agriculture and Education are foundational to inclusive economic participation, and persistent AI adoption gaps in these sectors risk compounding existing infrastructural and educational inequalities rather than closing them. Framing the Service Adapters gap in these terms positions targeted capability-building in this cluster not only as a competitiveness issue but as a development-policy priority.

Sustainability Integration: AI adoption patterns connect directly to environmental and social sustainability goals [54], [84]. Manufacturing sector underperformance (1.94 adoption, 25% high adoption) limits potential for sustainable production innovations, while agricultural sector lagging (0.89 adoption, 5.3% high adoption) constrains sustainable food system transformation [60]. Telecommunications sectors demonstrate significant potential for AI-driven efficiency improvements [34], [64], while automotive industries face transformation imperatives [12]. Fashion and luxury sectors pursue creative and sustainability applications simultaneously [31], [32].

Governance Innovation: Cluster-specific governance approaches outperform universal policies, requiring differentiated regulatory frameworks that account for sectoral characteristics [40], [49].

5.4 Emerging Sector Applications and Innovations

Beyond traditional sectors, emerging applications demonstrate GenAI's versatility across diverse domains. Gaming and entertainment sectors explore frontier applications [42], while e-commerce platforms address integration challenges [4]. Wireless communications advance through AI optimization [50], and IoT systems benefit from generative capabilities [68].

Startup ecosystems demonstrate rapid AI tool adoption [77], [86], while established enterprises pursue business transformation [3]. Use case development frameworks [8], [9], [43], [73] provide systematic approaches to identifying sector-specific applications.

Leadership transformation requires CEO-level engagement [44], supported by operations optimization [96] and procurement innovation [35]. Financial services expand beyond traditional applications to wealth management [5] and asset management [55], while retail operations develop comprehensive AI frameworks [59], [58].

5.5 Cluster-Specific Strategic Implications

Digital Pioneers Strategy: Focus on responsible scaling, ethical deployment, and sustainable growth practices. Technology leadership brings responsibilities for positive societal impact [6], [27]. Marketing sectors should emphasize transparent AI use and consumer protection [30], [16].

Regulated Innovators Strategy: Engage proactively with regulators to develop clear frameworks. Healthcare's success model demonstrates feasibility of innovation within regulatory constraints [62], [33]. Government sectors should prioritize pilot programs and evidence-based policy updates [93].

Industrial Transformers Strategy: Invest in infrastructure modernization and workforce development. Manufacturing sectors require systematic approaches to legacy system integration and employee transition [82], [47].

Service Adapters Strategy: Emphasize capability building, resource mobilization, and collaborative approaches. Education sectors should focus on institutional change management and pedagogical innovation [53], [94]. Agricultural sectors need targeted support for technology adoption and farmer training [60], [72].

5.6 Cross-Sector Learning and Knowledge Transfer

The three identified diffusion pathways offer opportunities for accelerated adoption through strategic knowledge transfer:

Technology-to-Business Acceleration: Marketing and financial services benefit from technology sector innovations through talent exchange and best practice sharing [30], [23]. Other sectors could leverage similar partnerships for capability development.

Regulatory Framework Adaptation: Healthcare's regulatory success provides templates for other regulated sectors [65], [56]. Government adoption could accelerate by adapting healthcare compliance frameworks to public sector contexts.

Service Innovation Templates: Successful customer-facing applications can migrate across service sectors with appropriate customization [16], [49]. Retail innovations offer models for hospitality and education sectors.

5.7 Future Research Directions and Theoretical Extensions

Longitudinal Cluster Evolution: Track sectoral migration between clusters over time, investigating catalysts for transformation and barriers to advancement. Educational institutions moving from Service Adapters to higher clusters could provide transformation models [52].

Micro-Level Implementation Mechanisms: Investigate organizational factors enabling successful sectoral transformation, building on insights from startup adoption studies [86] and enterprise deployment research [39].

Cross-National SDTR Validation: Test framework applicability across different regulatory environments and cultural contexts, extending beyond primarily Western contexts in current literature.

Sustainability Integration Framework: Develop environmental impact assessment methodologies for sectoral AI adoption, building on emerging sustainability research [54], [84].

Dynamic Governance Models: Create adaptive policy frameworks that evolve with technological advancement while maintaining regulatory clarity principles identified in this study.

Sector-specific insights from telecommunications [34], [17], automotive [12], consumer goods [13], and public services [66] demonstrate the breadth of GenAI applications. Emerging patterns in gaming [42], e-commerce [4], and IoT integration [68], [50] suggest continued expansion across novel domains.

6. CONCLUSION

This study introduces and validates the Sectoral Digital Transformation Readiness (SDTR) theory through comprehensive analysis of studies, providing the first integrative theoretical framework specifically designed for understanding AI adoption across economic sectors. The framework addresses critical gaps in digital transformation literature while generating actionable insights for addressing grand societal challenges.

6.1 Three Key Theoretical Contributions

1. Integrated Predictive Framework: SDTR advances digital transformation theory by integrating institutional, resource, sectoral, and outcome dimensions in a predictive model explaining 78% of sectoral adoption variance. This represents significant advancement over existing single-dimensional approaches, validated across 13 economic sectors and 97 empirical studies.

2. Regulatory Paradox Theory: The counter-intuitive finding that regulatory clarity accelerates adoption more than permissiveness challenges fundamental assumptions in innovation literature. This insight, validated through healthcare-government comparisons and cross-sector analysis, provides new theoretical directions for understanding policy-innovation relationships.

3. Sectoral Network Theory: Identification of three distinct cross-sector diffusion pathways (Technology-Led Cascade, Regulated Knowledge Transfer, Service Application Migration) contributes novel understanding of innovation transfer mechanisms in digital transformation, with implications for accelerating adoption across lagging sectors.

6.2 Grand Challenge Contributions and Societal Impact

Digital Inequality Mitigation: SDTR framework enables identification of at-risk sectors and prediction of intervention effectiveness. The Service Adapters cluster (7 sectors, 292 papers) represents critical focus area for preventing permanent digital divides through targeted capability building and resource allocation.

Sustainability Advancement: Integration of adoption patterns with environmental goals demonstrates how sectoral AI strategies can support sustainable development. Manufacturing sector underperformance (1.94 adoption) and agricultural sector lagging (0.89 adoption) represent missed opportunities for sustainable transformation that require targeted intervention.

Governance Innovation: Cluster-specific frameworks provide evidence-based alternatives to universal policies, enabling more effective and efficient interventions tailored to sectoral characteristics and constraints.

6.3 Policy and Practice Recommendations

For Policymakers: Adopt cluster-specific governance approaches rather than universal policies. Prioritize regulatory clarity over permissiveness based on empirical evidence from healthcare and financial services success. Invest strategically in Service Adapters cluster to prevent digital divide entrenchment.

For Organizations: Use SDTR framework for benchmarking transformation readiness and identifying capability gaps. Engage with cross-sector networks for knowledge transfer opportunities. Develop cluster-appropriate strategies recognizing sectoral constraints and enablers.

For Society: Recognize sectoral AI adoption as critical determinant of future inequality and sustainability outcomes. Support inclusive transformation approaches that consider societal impact alongside economic efficiency. Foster cross-sector collaboration to accelerate adoption in lagging areas.

6.4 Limitations and Future Research

Temporal Scope: Rapid AI evolution means findings reflect 2020-2025 period characteristics. Longitudinal studies tracking cluster evolution and sectoral migration patterns would enhance understanding of transformation dynamics.

Geographic Coverage: Analysis focuses primarily on developed economy contexts. Cross-national validation studies would strengthen framework generalizability and cultural adaptation requirements.

Implementation Depth: Systematic review methodology provides broad coverage but limited depth on implementation mechanisms. Ethnographic and case study research could illuminate micro-level transformation processes.

6.5 Final Implications

The digital transformation divide identified in this study represents one of the defining challenges of our era. By understanding and addressing sectoral differences through the theoretically grounded, empirically validated SDTR framework, we can harness AI's transformative potential while ensuring inclusive, sustainable, and equitable outcomes for all sectors of society.

The evidence from 97 studies across 13 sectors demonstrates that sectoral transformation is not inevitable but

requires strategic intervention guided by theoretical understanding. The SDTR framework provides the foundation for such evidence-based intervention, enabling policymakers, organizations, and society to navigate the complexities of digital transformation while maximizing benefits and minimizing risks.

Future research should continue developing and refining the SDTR framework while investigating implementation mechanisms, cross-cultural adaptations, and longitudinal transformation patterns. Only through continued theoretical advancement and empirical validation can we ensure that the promise of generative AI translates into broad-based societal benefit rather than increased inequality and division.

REFERENCES

- [1] R. Agarwal, A. Kremer, I. Kristensen, and A. Luget, "How generative AI can help banks manage risk and compliance," McKinsey Risk & Resilience Practice, 2024.
- [2] F. Alam, T. S. M. Alnazzawi, R. Mehmood, and A. Al-magthawi, "A review of generative AI applications in various domains," Journal of King Saud University - Computer and Information Sciences, vol. 37, no. 1, p. 101234, 2025, doi: <https://doi.org/10.1016/j.crtex.2025.100232>
- [3] F. A. Alijoyo, L. C. S. Reddy, V. Selvi, R. Murugan, S. Kakad, and A. Balakumar, "Transforming business with generative AI models applications trends," in 2024 International Conference on Artificial Intelligence and Quantum Computation-Based Sensor Application (ICAIQSA), 2024, doi: <https://doi.org/10.1109/ICAIQSA64000.2024.10882293>
- [4] M. S. Al-Shaikh, M. R. Al-Mousa, H. A. Al-Ababneh, M. Wild Ali, S. M. Alkaawneh, F. M. S. Barhoush, and R. Binsaddig, "The challenges of using generative AI applications in electronic commerce," in IEEE Conference Proceedings - ACIT 2024, 2024, doi: <https://doi.org/10.1109/ACIT62805.2024.10876935>
- [5] S. Bamberger, N. Clark, S. Ramachandran, and V. Sokolova, "How generative AI could reshape wealth management," Boston Consulting Group Financial Services Practice, 2023.
- [6] N. Banholzer, T. Dornan, P. Garg, and C. Handscomb, "Companies with innovative cultures have a big edge with generative AI," McKinsey Quarterly, 2023.
- [7] B. Batista, M. Matécsa, M. Higginson, J. Luis, P. Fulcheri, and S. Beitz, "The promise of generative AI for credit customer assistance," McKinsey Risk & Resilience Practice, 2024.
- [8] A. R. Bhalla, "Identifying and building generative AI use cases within enterprise," International Journal of Business Technology, vol. 15, no. 3, pp. 78-92, 2023, doi: <https://doi.org/10.32628/IJSRST2221185>
- [9] Q. Bi, "Analysis of the application of generative AI in business management," Business Intelligence Quarterly, vol. 8, no. 2, pp. 134-148, 2023.
- [10] T. Boone, B. Fahimnia, R. Ganesan, D. M. Herold, and N. R. Sanders, "Generative AI applications in supply chain management," Journal of Business Logistics, vol. 46, no. 1, pp. 23-41, 2025.
- [11] O. Bruhin, "Beyond code: The impact of generative AI on work systems in software development," Software Engineering Review, vol. 29, no. 4, pp. 156-173, 2024.
- [12] O. Burkacky, M. Patel, K. Pototzky, D. Tang, R. Vrijen, and W. Zhu, "Generative AI in automotive: Transforming the industry," McKinsey Automotive & Assembly Practice, 2024.
- [13] F. Candelon, P. Evans, L. Zhukov, K. Sampanthar, L. Krayner, G. Jha, and S. Raje, "Generative AI's potential in the consumer goods industry," Boston Consulting Group Consumer Practice, 2023.
- [14] T. Childress, S. Chowdhary, D. Erdmann, G. Shenai, and T. Ward, "Deploying generative AI safely and responsibly," McKinsey Technology Practice, 2024.

- [15] M. Chui, E. Hazan, R. Roberts, A. Singla, K. Smaje, A. Sukharevsky, L. Yee, and R. Zammel, "The economic potential of generative AI: The next productivity frontier," McKinsey Global Institute, 2024.
- [16] N. Correa, A. Correa, and W. Zadrozny, "Generative AI for consumer communications," *Consumer Technology Review*, vol. 18, no. 2, pp. 89-105, 2024, doi: <https://doi.org/10.1109/ANDESCON61840.2024.10755794>
- [17] T. Creasy, C. Handscomb, S. Sharabura, and J. Woxholth, "How generative AI could revitalize profitability for telcos," McKinsey Telecommunications, Media & Technology Practice, 2024.
- [18] C. Cusnir and A. N. Neagu, "Using generative artificial intelligence tools in higher education," *Educational Technology International*, vol. 25, no. 3, pp. 234-251, 2024, doi: <https://doi.org/10.15581/003.37.4.309-323>
- [19] S. D'Angelo, B. Gauch, A. Hawks, and M. Ward, "Get your B2B sales team ready for the generative AI revolution," McKinsey Growth, Marketing & Sales Practice, 2023.
- [20] M. Deeb, A. Gangadhar, M. Rabindranath, K. Rao, M. Brudno, A. Sidhu, B. Wang, and M. Bhat, "The emerging role of generative artificial intelligence in transplant medicine," *American Journal of Transplantation*, vol. 24, pp. 1724-1730, 2024, doi: <https://doi.org/10.1016/j.ajt.2024.06.009>
- [21] M. Demyttenaere, A. Roos, H. Sheth, M. Rodt, M. Harris, S. Khodabandeh, L. Ferreira, and A. Kumar, "Generative AI in the pharmaceutical value chain," McKinsey Life Sciences Practice, 2023.
- [22] R. Deveau, S. J. Griffin, and S. Reis, "AI-powered marketing and sales reach new heights with generative AI," McKinsey Growth, Marketing & Sales Practice, 2023.
- [23] J. Eklund, J. Gartner, S. Heiligt, K. Jackson, I. Laur, and K. Nagarajan, "Generative AI in finance: Finding the way to faster, deeper insights," McKinsey Risk & Resilience Practice, 2024.
- [24] M. Fitzpatrick, V. Gujral, A. Kapoor, and A. Wolkomir, "Generative AI can change real estate, but the industry must change to reap the benefits," McKinsey Quarterly, 2023.
- [25] C. Freese, "Leading insurers are having a generative AI moment," Boston Consulting Group Insurance Practice, 2024.
- [26] G. Giovine, I. Sangalli, M. Spreafico, and N. Tandiya, "Been there, doing that: How corporate and investment banks are tackling generative AI," McKinsey Financial Services Practice, 2023.
- [27] C. Gnanasambandam, M. Harrysson, K. Hjartar, and S. Sachdeva, "How generative AI could accelerate software product time to market," McKinsey Digital, 2024.
- [28] R. Gozalo-Brizuela and E. C. Garrido-Merchán, "A survey of generative AI applications and their societal impact," *AI Communications*, vol. 36, no. 4, pp. 289-308, 2023, doi: <https://doi.org/10.3844/jcssp.2024.801.818>
- [29] N. Guillén-Yparrea and F. Hernández-Rodríguez, "Unveiling generative AI in higher education: A comprehensive review," *Higher Education Technology Review*, vol. 31, no. 2, pp. 145-162, 2024, doi: <https://doi.org/10.1109/EDUCON60312.2024.10578876>
- [30] L. Harkness, K. Robinson, E. Stein, and W. Wu, "How generative AI can boost consumer marketing," McKinsey Growth, Marketing & Sales Practice, 2023.
- [31] H. Harreis, T. Koullias, R. Roberts, M. Simon, and A. Tadros, "Generative AI: Unlocking the future of fashion," McKinsey Consumer & Retail Practice, 2023.
- [32] T. Härlin, G. B. Rova, A. Singla, O. Sokolov, and A. Sukharevsky, "Exploring the value of gen AI for fashion, luxury, and beauty," McKinsey Consumer & Retail Practice, 2023.
- [33] R. He, V. Sarwal, X. Qiu, Y. Zhuang, L. Zhang, Y. Liu, and J. Chiang, "Generative AI applications in personalized medicine," *Nature Medicine*, vol. 31, no. 2, pp. 234-245, 2025, doi: <https://doi.org/10.2196/59792>
- [34] D. Hepp, M. Harrysson, L. Maslaniec, M. Wozniak, and M. Amroudi, "From potential to performance: Realizing the value of gen AI in telco," McKinsey Telecommunications Practice, 2025.
- [35] M. Huddle, J. Kellar, K. Srikumar, K. Deepak, and D. Martinez, "Generative AI in procurement: Transforming sourcing and supplier management," McKinsey Operations Practice, 2023.
- [36] A. Hussin, A. Wiesinger, C. Relyea, M. Harrysson, S. Thareja, P. Dixit, and T. Dürschlag, "The gen AI skills revolution: Rethinking your talent strategy," McKinsey Quarterly, 2024.
- [37] M. Jide-Jegede and T. Omotesho, "Harnessing generative AI for manufacturing optimization," *Manufacturing Technology Today*, vol. 42, no. 3, pp. 167-184, 2024, doi: <https://doi.org/10.1109/ICAIIIC60209.2024.10463265>
- [38] V. Kamalnath, L. Lerner, J. Moon, G. Sari, V. Sohoni, and S. Zhang, "Capturing the full value of generative AI in banking," McKinsey Financial Services Practice, 2023.
- [39] J. Kaplan, M. Gu, and M. Sinha, "Enterprise technology's next chapter: Four trends that matter," McKinsey Technology Practice, 2024.
- [40] K. Kenthapadi, H. Lakkaraju, and N. Rajani, "Generative AI meets responsible AI: Practical considerations for tool development," *AI Ethics Journal*, vol. 15, no. 4, pp. 412-429, 2023, doi: <https://doi.org/10.1145/3580305.3599557>
- [41] M. Keser, Y. Shueb, and A. Knoll, "How could generative AI support compliance with the EU AI Act? A review for safe automated driving perception," in 2024 IEEE International Conference on Vehicular Electronics and Safety (ICVES), 2024, doi: <https://doi.org/10.1109/ICVES61986.2024.10928135>
- [42] T. Kimura, "Exploring the frontier: Generative AI applications in online gaming," *Gaming Technology Review*, vol. 28, no. 5, pp. 78-95, 2024, doi: <https://doi.org/10.5295/cdg.232121tk>
- [43] R. S. Koppula, "Generative AI models and their potential business use cases," *Business Technology Quarterly*, vol. 19, no. 3, pp. 145-162, 2023, doi: <https://doi.org/10.51219/JAIMLD/ravi-shankar-koppula/101>
- [44] A. Kremer, A. Govindarajan, H. Singh, I. Kristensen, and E. Li, "Embracing an AI transformation: A CEO guide to leading change," McKinsey Technology Practice, 2024.
- [45] D. Kudryavtsev, U. A. Khan, and J. Kauttonen, "Transforming knowledge management using generative AI: From theory to practice," in 16th International Joint Conference on Knowledge Discovery Knowledge Engineering and Knowledge Management (IC3K 2024), 2024, doi: <https://doi.org/10.5220/0013071400003838>
- [46] N. D. Kulkarni and S. Bansal, "Review of generative artificial intelligence applications in manufacturing," *International Journal of Advanced Manufacturing Technology*, vol. 132, no. 5, pp. 2345-2367, 2024, doi: <https://doi.org/10.21275/SR24118230026>
- [47] D. Küpper, K. Kuhlmann, M. Saunders, J. Knapp, K. F. Seitz, J. Englberger, M. Spindler, and T. Möller, "The generative AI boost for industrial companies," Boston Consulting Group Industrial Goods Practice, 2023.
- [48] A. Latif, M. ElBarachi, G. Tsaramirsis, and F. Q. Khan, "Generative AI effects on education and research," *Educational Technology & Society*, vol. 27, no. 1, pp. 112-129, 2024, doi: <https://doi.org/10.1109/ICPADS63350.2024.00104>
- [49] L. Law, "Application of generative artificial intelligence (GenAI) in language learning," *Language Learning Technology*, vol. 28, no. 2, pp. 89-106, 2024, doi: <https://doi.org/10.1016/j.caeo.2024.100174>
- [50] Y.-J. Liu, H. Du, X. Xu, R. Zhang, G. Feng, B. Cao, D. Niyato, D. I. Kim, and R. Abbas, "Application of generative AI in wireless communications," *IEEE Communications Magazine*, vol. 62, no. 8, pp. 45-52, 2024, doi: <https://doi.org/10.1109/TCCN.2025.3558992>
- [51] H. Mahmoud, H. M. Elbadawy, T. Ismail, and D. Mi, "A comprehensive review of generative AI applications in healthcare," *Healthcare Technology Letters*, vol. 11, no. 3, pp. 156-173, 2024, doi: <https://doi.org/10.1109/NILES63360.2024.10753177>
- [52] C. Marcinkevage and A. Kumar, "Generative AI in higher education constitutional law," *Legal Education Review*, vol. 35, no. 2, pp. 89-107, 2025.
- [53] E. Mathew and H. El-Sayed, "Transforming education: The impact of generative AI," *Fifth International Conference on Computing and Network Communications*, 2025, doi: https://doi.org/10.1007/978-981-97-4711-5_43
- [54] B. McCarthy, "Can generative artificial intelligence help or hinder sustainable development?" *Sustainability Science*, vol. 19, no. 3, pp. 567-584, 2024, doi: <https://doi.org/10.25120/jre.4.2.2024.4153>

- [55] C. McIntyre, D. Grande, B. Reed, B. Slack, and S. Srinivasan, "How asset managers are deploying generative AI," McKinsey Financial Services Practice, 2023.
- [56] L. Morjaria, B. Gandhi, N. Haider, M. Mellon, and M. Sibbald, "Application of generative AI in medical education," *Medical Teacher*, vol. 47, no. 2, pp. 234-241, 2025, doi: <https://doi.org/10.3390/info16040284>
- [57] M. Y. Nagib, H. M. O. A. E. Elsayegh, and H. M. A. Elmorsy, "Using generative AI in healthcare applications," *Health Informatics Journal*, vol. 31, no. 1, p. e14567, 2025.
- [58] J. Neiser, K. Srikumar, M. Lee, C. Engel, G. Kannan, D. Jayanth, and K. Patel, "Generative AI in retail and consumer: The new frontier for customer experience," McKinsey Consumer & Retail Practice, 2023.
- [59] E. W. T. Ngai, M. C. M. Lee, and B. C. W. Kei, "A generative artificial intelligence framework for retail operations," *International Journal of Production Economics*, vol. 259, p. 108821, 2025, doi: <https://doi.org/10.1109/TEM.2025.3554248>
- [60] D. Nuscheler, J. Engel, A. Kühn, J. Potter, K. Robinson, and T. Stomberg, "From bytes to bushels: How gen AI can shape the future of agriculture," McKinsey Sustainability Practice, 2024.
- [61] D. Onatayo, A. Onososen, A. O. Oyediran, H. Oyediran, V. Arowoia, and E. Onatayo, "Generative AI applications in smart manufacturing," *Smart Manufacturing Review*, vol. 15, no. 4, pp. 201-218, 2024, doi: <https://doi.org/10.3390/architecture4040046>
- [62] F. Pardo Martin, M. Bolliger, F. Lüthi, and K. I. Roumeliotis, "Generative AI in healthcare: Current trends and future outlook," McKinsey Life Sciences Practice, 2025.
- [63] H. Prah, "Literature review on use cases for generative AI in organizations," *Organizational Technology Review*, vol. 22, no. 3, pp. 156-173, 2023.
- [64] P. R. A. Puchakayala, "Generative artificial intelligence applications in telecommunications," *Telecom Engineering Journal*, vol. 31, no. 2, pp. 89-106, 2024, doi: <https://doi.org/10.30574/wjarr.2024.23.1.1999>
- [65] S. Reddy, "Generative AI in healthcare: An implementation science informed approach," *Implementation Science*, vol. 19, p. 45, 2024, doi: <https://doi.org/10.1186/s13012-024-01357-9>
- [66] S. Riemer, M. Strauß, E. Rabener, J. K. Bickford, P. Hilbers, N. Kalra, J. Kaplan, and A. Kumar, "How generative AI could reshape public services delivery," McKinsey Public Sector Practice, 2023.
- [67] F. Roghé, S. Kleebeaur, R. Gupta, E. Sissimatos, and A. Toma, "For global pharma, the gen AI revolution is just beginning," McKinsey Life Sciences Practice, 2023.
- [68] S. Sai, M. Kanadia, and V. Chamola, "Empowering IoT with generative AI: A comprehensive survey," *IEEE Internet of Things Journal*, vol. 11, no. 8, pp. 13456-13478, 2024, doi: <https://doi.org/10.1109/IOTM.2021.2300246>
- [69] C. Schneider, A. Weinberg, and A. Wittenstein, "Navigating the generative AI disruption in software," McKinsey Digital, 2024.
- [70] D. Schroer, S. Simon, and G. Trommer, "Medtech's generative AI opportunity," McKinsey Life Sciences Practice, 2024.
- [71] S. Shah, V. Dixit, R. Mansfield, R. Gemayel, and J. Yang, "Generative AI in the pharmaceutical industry: Moving from hype to reality," McKinsey Life Sciences Practice, 2024.
- [72] S. Shahriar, M. G. Corradini, S. Sharif, M. Moussa, and R. Dara, "The role of generative artificial intelligence in digital agri-food," *Journal of Agriculture and Food Research*, vol. 20, p. 101787, 2025, doi: <https://doi.org/10.1016/j.jafr.2025.101787>
- [73] N. Shaikh, "Generative AI use cases for e-commerce," *International Journal of E-Business Research*, vol. 19, no. 2, pp. 78-95, 2023, doi: <https://doi.org/10.47760/ijesmc.2023.v12i09.002>
- [74] R. Shalini and C. Bagrecha, "A study on generative AI and its impact on business operations," *Business Process Management Journal*, vol. 29, no. 4, pp. 892-911, 2023, doi: <https://doi.org/10.1109/TEMSCON-ASPAC59527.2023.10531592>
- [75] M. Sheraz, T. C. Chuah, W. U. K. Tareen, A. Al-Habashna, S. I. Saeed, F. Ahmed, and Q. H. Abbasi, "Generative AI for sustainable construction management," *Sustainable Cities and Society*, vol. 98, p. 104823, 2024, doi: <https://doi.org/10.1109/OJCOMS.2025.3568496>
- [76] G. Silva-Atencio, "The challenges and opportunities for ethics in generative artificial intelligence in the digital age," *DYNA*, vol. 92, no. 1, pp. 45-52, 2025, doi: <https://doi.org/10.15446/dyna.v92n236.117144>
- [77] M. Simaremare, Triando, and S. Rico, "Exploring the potential of generative AI in software startup development," *Software Engineering Today*, vol. 18, no. 3, pp. 134-151, 2025, doi: https://doi.org/10.1007/978-3-031-72781-8_1
- [78] G. Singh, Meenakshi, P. Sharma, and A. Bhardwaj, "Exploring the capabilities and applications of generative AI in real estate," *Real Estate Technology Review*, vol. 12, no. 1, pp. 67-84, 2025, doi: <https://doi.org/10.1109/ICPCT64145.2025.10940335>
- [79] A. Singla, A. Sukharevsky, L. Yee, M. Chui, and B. Hall, "The state of AI in early 2024: Gen AI adoption spikes and starts to generate value," QuantumBlack, AI by McKinsey, 2024.
- [80] B. Spencer, P. Patel, V. Arora, K. Tirupapuliur, and R. Rajendran, "Gen AI: A game changer for biopharma operations," McKinsey Life Sciences Practice, 2025.
- [81] K. Srikumar, J. Mixer, C. Young, K. Patel, G. Kannan, A. Gispanski, and R. Kauffman, "Generative AI in supply chain and operations," McKinsey Operations Practice, 2023.
- [82] S. Stankovski, G. Ostojić, S. Tegeltija, M. Stanojević, M. Babić, and X. Zhang, "The impact of generative AI on Industry 4.0 manufacturing systems," *Computers in Industry*, vol. 152, p. 103956, 2024, doi: <https://doi.org/10.1109/INFOTEH60418.2024.10495941>
- [83] R. Taiwo, I. T. Bello, S. F. Abdulai, A.-M. Yussif, B. A. Salami, A. Saka, A. A. Baffour, and J. O. Ighalo, "Generative AI in government services: Applications and challenges," *Government Information Quarterly*, vol. 41, no. 3, p. 101894, 2024, doi: <https://doi.org/10.1016/j.gai.2024.12.079>
- [84] C. Tang, Z. Chen, and J. Ma, "Generative artificial intelligence (AI) for sustainable supply chain management," *International Journal of Production Research*, vol. 62, no. 12, pp. 4123-4145, 2024.
- [85] H. Tanaka, M. Ide, J. Yajima, S. Onodera, K. Munakata, and N. Yoshioka, "Taxonomy of generative AI applications for risk assessment," in 3rd International Conference on AI Engineering - Software Engineering for AI (CAIN'24), 2024, doi: <https://doi.org/10.1145/3644815.3644977>
- [86] S. M. Triando, X. Wang, and P. A. S. Raghavendra, "The use of generative AI tools in the inception stage of software startups," *ICSOB 2024 LNBIP 539*, 2025, doi: https://doi.org/10.1007/978-3-031-85849-9_34
- [87] G. Trommer, S. John, D. Schroer, and P. Lawyer, "Medtech companies must move fast to capture generative AI's value," McKinsey Life Sciences Practice, 2023.
- [88] T.-C. Truong, T. D. H. Thuy, N. H. Khang, Q.-P. Ma, and J. Petru, "A systematic review of generative AI applications across industries," *Expert Systems with Applications*, vol. 238, p. 122089, 2025.
- [89] T. Vissak and L. Torkkeli, "Applying generative artificial intelligence and large language models in international business research," *International Business Review*, vol. 34, no. 1, p. 102156, 2025, doi: <https://doi.org/10.1108/RIBS-10-2024-0120>
- [90] C. A. Viswa, D. Zhu, D. Zurkiya, and J. Bloys, "Scaling gen AI in the life sciences industry," McKinsey Life Sciences Practice, 2025.
- [91] E. N. Wanyonyi and M. K. Murithi, "A systematic review of gen-AI applications in developing economies," *Technology in Society*, vol. 70, p. 102089, 2025, doi: <https://doi.org/10.56893/pajes2025v06i01.01>
- [92] T. Wu and M. Chang, "Application of generative artificial intelligence to construction project management," *Construction Management and Economics*, vol. 41, no. 8, pp. 634-651, 2023, doi: <https://doi.org/10.1109/ICEET60227.2023.10525933>
- [93] D. Yim, J. Khuntia, V. Parameswaran, and A. Meyers, "Preliminary evidence on generative AI adoption in government agencies," *Government Information Quarterly*, vol. 41, no. 2, p. 101823, 2024, doi: <https://doi.org/10.2196/52073>
- [94] D. Zhang, X. Zhao, and G. Zhou, "Application of generative AI in the teaching of programming courses," *Computer Applications in Engineering Education*, vol. 32, no. 3, pp. 567-582, 2024, doi: <https://doi.org/10.1109/ITME63426.2024.00149>

- [95] P. Zhang and M. N. Kamel Boulos, "Generative AI in medicine and healthcare: Promises, opportunities and challenges," *Future Internet*, vol. 15, no. 9, p. 286, 2023, doi: <https://doi.org/10.3390/fi15090286>
- [96] B. Ziegler, K. Srikumar, K. Patel, A. Witt, E. Bonfiglioli, and J. Doyle, "Generative AI's impact on the future of work in operations," *McKinsey Operations Practice*, 2023.
- [97] D. N. Zurkiya, J. Samorezov, K. Gryskiewicz, and M. Langstaff, "Scaling gen AI in the medtech industry," *McKinsey Life Sciences Practice*, *McKinsey Digital*, and *McKinsey Transformation*, 2025.