Inter-Domain Adaptation Mechanisms of AI Innovation: How AI Breaks Through Sectoral Barriers (2022-2026)

Abstract

The cross-domain expansion of artificial intelligence (AI) is not a simple technical transplantation but a systematic adaptation process that aligns AI capabilities with domain-specific rules, needs, and contexts. This review synthesizes 9 key studies (2022-2026) to identify three core inter-domain adaptation mechanisms: technical adaptation (reconfiguring AI architectures to fit domain-specific data and task characteristics), scenario adaptation (tailoring AI functions to match sectoral application scenarios and user demands), and governance adaptation (aligning AI systems with domain regulatory frameworks and ethical norms). By analyzing how these mechanisms enable AI to overcome "domain incompatibility" in healthcare, quantum science, digital commerce, cybersecurity, and finance, the paper reveals that successful cross-domain AI relies on the dynamic balance between technical generality and domain specificity. The findings provide a new analytical framework for understanding AI's cross-sectoral diffusion, offering guidance for researchers designing adaptable AI systems and practitioners implementing AI across diverse fields.

1 Introduction

AI's transformative potential is increasingly contingent on its ability to adapt to the unique contexts of different domains [1][10]. For example, a lung nodule segmentation algorithm (healthcare) cannot be directly applied to microservice vulnerability detection (cybersecurity) without reconfiguring its feature extraction logic [1][5], nor can a financial portfolio optimization model (finance) be transplanted to digital commerce without adjusting for user privacy constraints [10][3]. However, existing research focuses more on AI's domain-specific performance than on the adaptation mechanisms that enable its cross-sectoral diffusion [2][7]. This review addresses this gap by synthesizing recent literature (2022-2026) to unpack the inter-domain adaptation mechanisms of AI innovation. By integrating findings from five diverse sectors, this paper aims to explain how AI systems adjust to domain-specific data, scenarios, and governance requirements, providing a holistic understanding of how AI breaks through sectoral barriers.

2 Core Inter-Domain Adaptation Mechanisms of AI Innovation

2.1 Technical Adaptation: Reconfiguring Architectures for Domain-Specific Data and Tasks

Technical adaptation is the foundational mechanism through which AI systems adjust their core architectures, algorithms, and data processing pipelines to fit the unique data characteristics and task requirements of target domains. This adaptation resolves the "technical mismatch" between generic AI frameworks and domain-specific needs. In healthcare, lung nodule segmentation requires handling 3D medical images with high spatial heterogeneity— a task that standard computer vision models struggle with. Chang et al. [1] addressed this through technical adaptation: reconfiguring path aggregation modules to optimize 3D feature transmission and integrating dual attention mechanisms to enhance sensitivity to small, irregular nodules. This adaptation of computer vision techniques to medical imaging data enabled PDU-Net to outperform generic segmentation models. In quantum science, Wu et al. [2] faced the challenge of modeling complex, unstructured quantum states that lack labeled data. Their technical adaptation involved customizing unsupervised learning algorithms to process high-dimensional quantum data, abandoning traditional supervised learning paradigms that rely on labeled samples. In finance, Li and Liu [10] adapted LSTM models—originally designed for natural language processing—by adjusting sequence window sizes and activation functions to fit the volatility and periodicity of financial time-series data, enabling accurate market trend prediction for portfolio optimization. Technical adaptation thus ensures that AI’s core capabilities are reconfigured to match the data and task characteristics of target domains.

2.2 Scenario Adaptation: Tailoring Functions to Domain-Specific Application Contexts

Scenario adaptation involves customizing AI’s functional design, interaction modes, and output forms to align with the practical application scenarios and user demands of specific domains. This mechanism ensures that AI systems are not only technically feasible but also practically useful in real-world contexts. In digital commerce, Yi [3][8] focused on the scenario of cross-channel marketing, where retailers need to balance user privacy with personalized targeting. The scenario adaptation here involved designing federated learning frameworks that output aggregated marketing insights rather than individual user data, and integrating zero-knowledge verification to enable creator monetization without exposing user behavior details. For SMEs in digital commerce, Yi [7] adapted AI infrastructure to the scenario of limited technical resources: developing a multi-tenant architecture with standardized APIs that allow SMEs to access advanced AI capabilities without building in-house systems. In cybersecurity, Zhou [4] addressed the scenario of microservice vulnerability patch planning, where IT teams, security vendors, and business units have conflicting priorities (e.g., security vs. operational continuity). The scenario adaptation involved using multi-agent reinforcement learning to generate patch plans that balance cost, efficiency, and business impact, rather than simply prioritizing technical security. In healthcare, the scenario of medical imaging diagnosis demands AI outputs that integrate seamlessly with clinical workflows—Chang et al. [1] implicitly addressed this through PDU-Net’s design, which generates segmentation results compatible with existing medical image analysis systems, enabling radiologists to use AI insights without disrupting clinical routines. Scenario adaptation thus ensures that AI systems fit seamlessly into the practical application contexts of target domains.

2.3 Governance Adaptation: Aligning Systems with Domain-Specific Regulatory and Ethical Norms

Governance adaptation is a critical mechanism that aligns AI systems with the regulatory frameworks, ethical standards, and compliance requirements of target domains. This adaptation resolves legal and ethical barriers to cross-domain AI adoption. In healthcare, where data privacy is governed by strict regulations (e.g., HIPAA, GDPR), medical AI systems like PDU-Net [1] require governance adaptation—ensuring that 3D medical image processing complies with patient data protection laws, such as anonymizing patient identifiers before AI analysis. In digital commerce, Yi [3][8] addressed regulatory requirements for cross-channel data sharing by adapting AI frameworks with differential privacy and federated learning—technologies that inherently comply with data minimization and purpose limitation principles. In financial ESG governance, Liu [6] highlighted the need for governance adaptation in AI tools designed for SMEs: ensuring that ESG optimization models align with sustainable finance regulations and disclosure requirements, enabling SMEs to improve their ratings while meeting regulatory obligations. Even in quantum science, Wu et al. [2] noted that governance adaptation would be necessary for cross-institutional collaboration, as quantum research data may involve intellectual property and national security considerations. In cybersecurity, Zhou [5] adapted the hybrid SAST-DAST-SCA-IAST framework to comply with industry-specific security standards (e.g., ISO 27001), ensuring that vulnerability prioritization aligns with regulatory requirements for risk management. Governance adaptation thus ensures that AI systems operate within the legal and ethical boundaries of target domains.

3 Dynamics of Inter-Domain Adaptation: Trade-Offs and Synergies

3.1 Key Trade-Offs in Adaptation

Inter-domain AI adaptation involves inherent trade-offs that shape implementation strategies: first, **generality vs. specificity**—over-adapting to a single domain may reduce AI's scalability to other sectors [1][10]. For example, a lung nodule segmentation model highly optimized for medical imaging may be difficult to adapt to other computer vision tasks. Second, **performance vs. compliance**—strengthening governance adaptation to meet regulatory requirements may slightly compromise AI's predictive accuracy [3][1]. For instance, anonymization of medical images (governance adaptation) could reduce the precision of lung nodule segmentation in healthcare. Third, **innovation vs. usability**—overly complex technical adaptations may increase user adoption barriers [7][4]. For example, a highly customized AI patch planning system may be too complex for small businesses to operate. Balancing these trade-offs is critical for successful cross-domain adaptation.

3.2 Synergies Between Adaptation Mechanisms

The three adaptation mechanisms are not independent but mutually reinforcing: technical adaptation provides the foundational capability to fit domain data [1][2], scenario adaptation ensures practical utility [4][8], and governance adaptation enables legal and ethical acceptance [3][1]. For example, Yi's [8] privacy-enhanced ad targeting framework for social e-commerce relies on technical adaptation (federated learning algorithm customization), scenario adaptation (aligning with creator monetization needs), and governance adaptation (complying with privacy regulations)—the synergy of these mechanisms enables the framework's cross-domain success. Similarly, Zhou's [5] hybrid security framework combines technical adaptation (integrating multiple testing techniques), scenario adaptation (prioritizing risk based on business context), and governance adaptation (complying with security standards)—this synergy ensures that the framework is technically advanced, practically useful, and regulatory compliant.

4 Practical Implications and Future Directions

For researchers, the findings highlight the need to design AI systems with "adaptability by design"—incorporating modular architectures that facilitate technical reconfiguration [1][5], user-centric design principles for scenario alignment [7][1], and compliance-by-design features that simplify governance adaptation [3][8]. For practitioners, the adaptation mechanisms offer a actionable roadmap: when implementing cross-domain AI, first conduct a domain audit to identify data/task characteristics (technical adaptation needs), then map application scenarios and user demands (scenario adaptation priorities), and finally align with regulatory and ethical norms (governance adaptation requirements). Policymakers can support inter-domain adaptation by promoting standardized data formats (reducing technical adaptation costs) [2][10], developing cross-sectoral privacy frameworks (simplifying governance adaptation) [3][8], and funding inclusive AI tools that lower scenario adaptation barriers for SMEs [6][7].

Future research should focus on three areas: first, developing quantitative metrics to assess adaptation effectiveness (e.g., adaptation cost, domain fit, compliance level); second, exploring AI-driven adaptation tools that automate parts of the inter-domain adjustment process (e.g., modular algorithm libraries, scenario-aware configuration platforms); third, investigating cross-domain adaptation in emerging fields (e.g., climate science, smart cities) to test and expand the framework. Additionally, case studies of failed cross-domain AI implementations could provide insights into adaptation failures, helping to refine best practices.

5 Conclusion

This review synthesizes recent literature to identify the core inter-domain adaptation mechanisms of AI innovation: technical adaptation, scenario adaptation, and governance adaptation. These mechanisms enable AI systems to overcome domain-specific barriers related to data/tasks, application contexts, and regulatory norms, facilitating cross-sectoral diffusion and value creation. While adaptation involves trade-offs between generality and specificity, performance and compliance, and innovation and usability, the synergy of the three mechanisms is critical for successful cross-domain AI implementation. By understanding and leveraging these adaptation mechanisms, researchers, practitioners, and policymakers can accelerate the responsible and effective adoption of AI across healthcare, quantum science, digital commerce, cybersecurity, finance, and beyond—unlocking AI's full transformative potential.

References

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