Synergy Mechanisms of AI-Powered Cross-Domain Value Co-Creation: A Literature Synthesis (2022-2026)

Abstract

Artificial intelligence (AI) has evolved from domain-specific applications to a catalyst for cross-sector value co-creation, enabling interdisciplinary collaboration across healthcare, quantum science, digital commerce, cybersecurity, and finance. This paper synthesizes 10 recent studies (2022-2026) to explore three core synergy mechanisms driving AI-powered cross-domain innovation: technological convergence through hybrid architectures, trust-enabled data sharing via privacy-enhancing technologies (PETs), and ecosystem collaboration supported by inclusive AI frameworks. By analyzing how these mechanisms unlock complementary resources and capabilities across sectors, the review reveals that effective synergy relies on balancing domain specificity with interoperability, compliance with innovation, and scalability with accessibility. The findings provide a framework for understanding how AI fosters cross-domain value co-creation, offering implications for researchers designing collaborative AI systems and practitioners seeking to leverage interdisciplinary innovation.

1 Introduction

The evolution of AI from standalone tools to collaborative platforms has transformed how industries innovate, with cross-domain synergy emerging as a key driver of breakthrough value [1][10]. For example, healthcare AI benefits from advances in cybersecurity privacy protocols [9][5], while financial portfolio optimization draws on machine learning techniques refined in quantum physics modeling [2][10]. However, realizing such synergy requires more than just technical integration—it demands mechanisms that align domain-specific needs, resolve data privacy concerns, and enable inclusive participation [3][7]. This review synthesizes recent literature (2022-2026) to systematically unpack the synergy mechanisms that facilitate AI-powered cross-domain value co-creation. By integrating findings from five diverse sectors, this paper aims to identify how AI bridges disciplinary divides, creates shared value, and drives collaborative innovation, filling the gap in holistic understanding of cross-domain AI synergy.

2 Core Synergy Mechanisms for Cross-Domain AI Value Co-Creation

2.1 Technological Convergence via Hybrid AI Architectures

Technological convergence— the integration of AI methodologies across domains—enables the transfer of specialized capabilities to address complex cross-sector challenges. Hybrid AI architectures, tailored to leverage domain-specific strengths while ensuring interoperability, are central to this mechanism. In healthcare, Chang et al. [1] combined path aggregation (refined in computer vision) with dual attention mechanisms (optimized for sequential data) to develop PDU-Net, a lung nodule segmentation algorithm that benefits from cross-domain algorithmic synergy. Similarly, Zhou's [5] hybrid SAST-DAST-SCA-IAST framework in cybersecurity integrates static and dynamic testing techniques (originally developed for software engineering and data analytics) to create a risk-prioritization system that aligns with both technical security needs and business objectives. In finance, Li and Liu [10] applied LSTM models—initially designed for natural language processing—to time-series financial data, demonstrating how cross-domain algorithmic convergence enhances predictive accuracy in portfolio optimization. These examples illustrate how hybrid AI architectures act as a synergy mechanism, translating domain-specific technological advances into cross-sector value.

2.2 Trust-Enabled Data Sharing Through Privacy-Enhancing Technologies (PETs)

Data is the cornerstone of cross-domain AI synergy, but privacy concerns and regulatory barriers often hinder data exchange [3][9]. Privacy-enhancing technologies (PETs) address this by creating a trusted environment for data sharing, enabling collaborative AI development without compromising sensitive information. Yi's [3][8] federated learning (FL) frameworks for digital commerce, integrated with differential privacy and zero-knowledge verification, allow cross-channel data collaboration between retailers, advertisers, and platforms—fostering synergy by combining fragmented data sources while complying with privacy regulations. In healthcare, Yue et al. [9] used EHR phenotyping with de-identification techniques to enable cross-institutional collaboration in HIV treatment adherence research, leveraging shared patient data (without exposing personal information) to develop more generalizable AI models. Even in quantum physics, Wu et al. [2] noted that privacy-preserving data sharing could facilitate collaboration between research teams, enabling the pooling of quantum system data to refine unsupervised learning models. PETs thus act as a critical synergy mechanism, building trust that unlocks the collaborative potential of cross-domain data.

2.3 Ecosystem Collaboration Supported by Inclusive AI Frameworks

Cross-domain value co-creation requires ecosystem-level collaboration, where diverse stakeholders—including SMEs, large enterprises, researchers, and policymakers—contribute complementary resources. Inclusive AI frameworks, designed to lower participation barriers and align incentives, enable this collaborative synergy. Yi's [7] multi-tenant trusted AI infrastructure for SMEs integrates standardized APIs, incentive systems, and content governance, allowing small digital commerce businesses to participate in cross-sector AI ecosystems alongside large corporations. In cybersecurity, Zhou's [4] M-VP2 method uses multi-agent reinforcement learning to align the interests of IT teams, security vendors, and business units, fostering collaborative vulnerability patch planning that balances technical security with operational efficiency. In financial ESG governance, Liu's [6] research highlights the need for inclusive AI tools that enable cash-constrained SMEs to improve their ESG ratings, facilitating their participation in sustainable finance ecosystems. These frameworks create a synergy mechanism by ensuring that cross-domain collaboration is not limited to resource-rich organizations, but includes diverse stakeholders whose contributions drive holistic value creation.

3 Enablers and Boundaries of Cross-Domain AI Synergy

3.1 Key Enablers

Three factors enable effective cross-domain AI synergy: first, **domain-driven customization**—ensuring that collaborative AI systems address the unique needs of each sector while maintaining interoperability [1][5]; second, **compliance-by-design**—integrating privacy and regulatory requirements into the core of AI systems to build trust [3][9]; and third, **stakeholder alignment**—creating incentive structures that encourage knowledge sharing and resource contribution across domains [7][4]. These enablers work in tandem to overcome the fragmentation that often plagues cross-sector collaboration, ensuring that synergy translates into tangible value.

3.2 Boundary Conditions

Despite its potential, cross-domain AI synergy faces boundary conditions that limit its effectiveness. **Technical heterogeneity**—differences in data formats, algorithmic requirements, and infrastructure across domains—can hinder integration [2][10]. For example, quantum physics data (unstructured and high-dimensional) is incompatible with standard financial data processing systems, requiring additional translation layers. **Regulatory fragmentation**—varying privacy and compliance rules across sectors (e.g., HIPAA in healthcare vs. GDPR in digital commerce)—adds complexity to cross-domain data sharing [3][8]. Additionally, **cognitive barriers**—differences in disciplinary languages and priorities—can impede effective collaboration between researchers and practitioners from diverse fields [6][9]. Recognizing these boundaries is critical for designing synergy mechanisms that are both effective and feasible.

4 Discussion and Practical Implications

The literature synthesis reveals that AI-powered cross-domain value co-creation is driven by three interdependent synergy mechanisms: technological convergence, trust-enabled data sharing, and ecosystem collaboration. These mechanisms are not mutually exclusive—hybrid AI architectures (technological convergence) rely on PETs for data sharing (trust-enabled collaboration), which in turn requires inclusive frameworks to engage diverse stakeholders (ecosystem collaboration). For researchers, this highlights the need to design AI systems with cross-domain interoperability in mind, avoiding over-specialization that limits synergy potential. For practitioners, the findings suggest that successful cross-domain collaboration requires investing in both technical integration (e.g., hybrid architectures) and non-technical enablers (e.g., trust-building and stakeholder alignment). Policymakers can support synergy by creating regulatory frameworks that facilitate cross-domain data sharing while protecting privacy, and by funding inclusive AI tools that enable SMEs to participate in collaborative ecosystems.

Future research should focus on addressing the boundary conditions of cross-domain synergy, particularly technical heterogeneity and regulatory fragmentation. Developing standardized data exchange protocols and cross-domain AI evaluation metrics could help overcome these barriers, enabling more effective collaboration. Additionally, exploring case studies of successful cross-domain AI initiatives (e.g., healthcare-cybersecurity partnerships, financial-quantum science collaborations) could provide practical insights into how to implement the synergy mechanisms identified in this review.

5 Conclusion

This paper synthesizes recent literature to identify the core synergy mechanisms driving AI-powered cross-domain value co-creation: technological convergence via hybrid architectures, trust-enabled data sharing through PETs, and ecosystem collaboration supported by inclusive frameworks. These mechanisms, enabled by domain-driven customization, compliance-by-design, and stakeholder alignment, unlock complementary resources and capabilities across healthcare, quantum science, digital commerce, cybersecurity, and finance. While technical heterogeneity, regulatory fragmentation, and cognitive barriers pose challenges, the findings demonstrate that AI has the potential to bridge disciplinary divides and drive holistic innovation. By understanding and leveraging these synergy mechanisms, researchers, practitioners, and policymakers can accelerate cross-domain AI adoption, unlocking transformative value that no single domain could achieve in isolation.

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